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Volatility Spillover in the Cryptocurrency market: Categorization of the Cryptocurrency Market Based on their Primary Use and the Effects of COVID-19

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Volatility Spillover in the Cryptocurrency market: Categorization of the Cryptocurrency Market Based on their Primary Use and the Effects of COVID-19

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Abstract

Utilizing the generalized spillover index developed by Diebold and Yilmaz (2009, 2012), we investigate the volatility connectedness between an index consisting of nine selected cryptocurrencies, S&P 500, Gold, and Copper. Furthermore, we study the connectedness and volatility spillover within the nine cryptocurrencies in the perspective of the categorization of the cryptocurrency market developed by Corbet et al. (2020b). To our knowledge, this is the first study investigating the connectedness between these categories. Lastly, we analyze the initial effect of the COVID-19 pandemic by using an extended set of data to June 2020 on the connectedness within the cryptocurrency market. We also test the connectedness between the cryptocurrency market, S&P 500, and Gold during the same period.

We find that the cryptocurrency market has a weak connectedness with other financial markets, indicating that most of the volatility comes from within the cryptocurrency market. When studying the volatility spillover within the cryptocurrency market, in the perspective of categorizations, our results show that most of the volatility is within the respective categories. Adding to this, there are some key differences in the relationship of the categories. Finally, the COVID-19 pandemic increased the volatility and the spillovers across all markets. However, the effects do not affect the results for the cryptocurrencies substantially.

Acknowledgement

Most importantly, we want to express our deepest gratitude to our supervisor Adam Walter Winegar for his insights and support throughout this process. His knowledge and constant feedback have led to a better overall result and improved our understanding of the topic. Adding to this, we want to thank our families for constantly motivating and supporting us during our work.

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List of Abbreviations

Abbreviation		Full
ADF	-	Augmented Dickey-Fuller
AIC	-	Akaike's information criterion
ARCH	-	Autoregressive conditional heteroscedasticity
dApp	-	Decentralized application
DLT	-	Distributed ledger technology
EWI	-	Equally weighted index
FEVD	-	Forecast error variance decomposition
FOMC	-	Federal Open Market Committee
FPE	-	Final predictor error
GARCH	-	Generalized autoregressive conditional heteroscedastic
HQ	-	Hannan-Quinn
ICO	-	Initial Coin offering
JB	-	Jarque-Bera
KPPS	-	Koop, Potter, Pesaran, Shin
OTC	-	Over the counter
PM	-	Portmanteau
PP	-	Phillips-Perron
SC	-	Schwarz criterion
VAR	-	Vector autoregression
VWI	-	Value weighted index
WHO	-	World Health Organization

1 Introduction

In recent years, cryptocurrencies have attracted considerable attention from investors, media, and the public in general (Corbet et al., 2019) and they have rapidly grown into an important element of the global financial market (Gajardo et al., 2018). A cryptocurrency is a decentralized digital asset and as opposed to traditional flat currency, cryptocurrency provides a payment system that ensures anonymity, low cost, and fast peer-to-peer transactions based on cryptographic protocols (Yi et al.,2018). From the creation of the first cryptocurrency Bitcoin in 2009 by Nakamoto (2008), the number of cryptocurrencies have now surpassed 5500[1] and have been consistently increasing.

Earlier studies have reported the cryptocurrency market to be a volatile market and a significant portion of the purchases of cryptocurrency are categorized as speculation (Fry & Cheah, 2016). Due to the growing number of new cryptocurrencies, as well as the increasing market capitalization of the cryptocurrency market (Ji et al., 2019; Yi et al., 2018), a significant amount of research has been done to investigate the cryptocurrency market and how it interacts with other markets, in terms of both return and volatility (see, among others, Bouri et al., 2017; Corbet et al., 2018; Dyhrberg, 2016; W. Liu, 2019; Y. Liu & Tsyvinski, 2018).

Volatility spillover is commonly referred to as cross-market volatilities, which explains how the volatility within a market could be influenced by volatilities of other financial markets across time (Ke et al., 2010). The direction and magnitude of volatility spillover may be time-varying, and could give an early indication of a potential crisis (Diebold & Yilmaz, 2012). The focus of earlier studies of volatility spillover on cryptocurrencies has primarily been between Bitcoin and other financial markets (Bouri et al., 2017; Dyhrberg, 2016; Gajardo et al., 2018). Further, previous literature focusing on the spillover within the cryptocurrency market has mainly focused on high market capitalization cryptocurrencies (Antonakakis et al., 2019; Ji et al., 2019). Earlier studies also find that the cryptocurrency market is an interdependent market (Ji et al., 2019) fairly isolated

[1] The number are collected by Coinmarketcap.com as of 15.06.2020.

from market shocks and have a weak connectedness with popular financial markets (Corbet et al., 2018). There are at least two different reasons for why volatility spillover is an important subject. First, investigating spillover effects between financial markets could lead to better investment- and trading strategies for investors involving different asset classes in a portfolio. In return, this would allow for more efficient capital allocation. Second, it increases our understanding of both the existence and extent of potential contagion effects between markets. This brings us to our first research question:

"How connected, in terms of volatility spillover, is the cryptocurrency market when compared to other financial markets?"

If most of the volatility is generated from within the cryptocurrency market, then it is important to understand the spillover effects within the cryptocurrency market. Furthermore, although there has been research on the connectedness within the cryptocurrency market (e.g Ji et al., 2019; Yi et al., 2018), there has not been any on the effects of primary use of a cryptocurrency and its relation to volatility spillover. Thus, to analyze the volatility spillover within the cryptocurrency market from a different approach, we use the classifications of Corbet et al. (2020b).

As the cryptocurrency market has increased, the applications of the underlying technology have developed as well. Corbet et al. (2020b) explained in their study that the cryptocurrency market could be divided into three categories based on their primary use. The first category is described as the *Currency* category where the primary use of the cryptocurrency is storage and transfer of value. The second is the *Protocol* category, which works as a platform for decentralized applications to be built upon. The final category is the *dApp*, which is the decentralized applications built upon the platform of the protocols. Additionally, they explain that the cryptocurrency market frequently is viewed as single market existing of identical assets, while there in fact are key differences between the categories in the market. Therefore, it will be incorrect to view all digital assets in the cryptocurrency market as identical assets. This leads to our second main research question:

"To what extent does the volatility spillover between cryptocurrencies vary with the main focus on their primary usage?"

Analyzing if the primary use of a cryptocurrency affects the connectedness with other cryptocurrencies with the same primary use, can help an investor diversify by investing based on the categories. Adding to this, it can contribute to understand the behavior of the categories in terms of volatility, especially the relationship between dApp cryptocurrencies connectedness to the protocol they are built on.

During the writing of this thesis, the COVID-19 virus developed from a virus contained in China to a worldwide pandemic. The effects of the pandemic have led to a global crisis. In general, empirical evidence imply that connectedness in volatility during a crisis period is time-varying and significant (Shahzad et al., 2018; D. Zhang & Broadstock, 2018). Due to the large effect the pandemic has had and still has on the world-economy (Corbet et al., 2020a), it is important to investigate if and how the effects extend to the cryptocurrency market. In the final analysis of our thesis, we examine the following question:

"How has the COVID-19 pandemic affected the volatility spillover and connectedness within the cryptocurrency market, as well as the connectedness between the cryptocurrency market and other financial markets?"

Utilizing the spillover index developed by Diebold and Yilmaz (2009, 2012) we find that the connectedness between the cryptocurrency market, S&P 500, and Gold without the inclusion of the COVID-19 dates is weak, indicating that the cryptocurrency market is an interdependent market. When investigating the cryptocurrency market, it appears from the results that there is a relationship between market capitalization and connectedness with the market, where higher market capitalization cryptocurrencies has a stronger connectedness to the other cryptocurrencies. As a new contribution to the research of the volatility spillover within the cryptocurrency market, we focus on the categorization of the cryptocurrency market. We find that the Protocol category, on average, has the strongest connectedness to the other categories. The results show that there is connectedness between Ethereum, and the decentralized applications built upon them. When indexing the categories, the results show that the Protocol category is the strongest contributor to uncertainty in the market, being a net transmitter of volatility to both dApps and Currencies. We also find a stronger relationship between Protocol and dApps and the results indicates that most of the volatility comes from within each subgroup. Lastly, as new contribution building on prior work, it appears from the results that the overall connectedness between the financial markets increases when including the COVID-19 dates. However, the increase in connectedness is mostly driven by the increased connectedness between the S&P 500 and Gold, implying that the cryptocurrency market is still an interdependent market even when including the initial phase of COVID-19.

Cryptocurrencies have a potentially unique characteristic in that they not only represent a financial asset but also have a variety of different uses. These uses include storage of value, transfer of value, and operational purposes. Thus, it is important to differentiate among cryptocurrencies according to their main purposes. Therefore, by understanding the relationship of volatilities among cryptocurrencies along this given dimension, we can hope to learn something additional about financial markets in general. Specifically, how such things as an asset's use and user-base, as opposed to its financial characteristics, affects movements in their prices.

Our result could apply to a wider set of assets including the real estate market, which is another asset class often viewed as a single broad category but takes on several different categorizations, e.g., private real estate, public real estate, industrial real estate etc. Inside these subcategories, there are even further subcategories like houses versus condominiums as well as different potential sets of buyers. To our knowledge, there has been few studies of how the uses of these types of assets affect their market behaviors. Even more broadly, Herskovic et al. (2016) find that most volatility is idiosyncratic and that this holds for each category, subcategory, and even individual stocks. This shows the potential importance of differentiating between these categories and the potential inaccuracy of treating them as identical. As this aspect of the cryptocurrency market is not very well known to the public, this master thesis contributes to further research on this particular field. Moreover, it could help rethink how to classify financial assets in general and encourage further studies on categorizations of other financial markets.

The structure of this thesis is as follows. In chapter 2, we give a brief review of related literature, including the discussion on volatility, volatility spillover, volatility spillover between financial markets, and volatility spillover within the cryptocurrency market. Chapter 3 gives a brief explanation of the cryptocurrency market, blockchain technology, an explanation of the different categories, and the selection of the cryptocurrencies. In chapter 4, the methodology used to estimate the volatility spillover is presented. Chapter 5 presents the data set used in the thesis, as well as the descriptive statistical tests. In chapter 6, the empirical results are presented with a discussion of the analyses. Finally, the conclusion is presented in chapter 7.

2 Literature Review

This master thesis covers several different subjects considering financial theory, and a full discussion about earlier studies conducted on these subjects is presented below. As mentioned in the introduction, the model used in this master thesis is the volatility spillover index constructed by Diebold and Yilmaz (2009), and the model is used to measure the volatility spillover within the cryptocurrency market and between the cryptocurrency market and other financial markets. We have divided the review into three parts – volatility spillover, volatility spillover between financial markets, and volatility spillover within the cryptocurrency market.

2.1 Volatility spillover

To understand what volatility spillover is and what it measures, we give a brief overview of the definition of volatility and its frequent and necessary use from a financial market context.

2.1.1 Volatility

Volatility in a financial framework is defined as a measure of variation in prices or returns of financial instruments over time (Ke et al., 2010). Financial volatility is often used as a measure of risk e.g. – the riskiness of a stock or a portfolio of stocks. To further simplify the discussion, we use the volatility of stock prices as an example. In most cases, the higher the volatility, the riskier the financial asset is viewed. In finance and economics, volatility plays a central role and is one of the most researched and developed parts of financial econometrics (Molnár, 2012). The most common measure of volatility is the variance of a stock price, an easily calculated measure. One issue with the variance measurement is that it only captures the average volatility over a predefined period (Molnár, 2012). Given the nature of our question, in this master thesis we focus on daily prices and, thus it is crucial that we capture the daily volatility of these prices. Therefore, throughout this thesis, we use the range based volatility estimate developed by Garman &

Klass (1980),which estimates daily volatility via the readily available information of high, low, open and closing prices.[2]

2.1.2 Definition of volatility spillover

Volatility spillover is a highly researched subject in the finance literature. Ke et. al. (2010) explain that over time, the volatility of a financial market may be affected by volatilities of other financial markets and that the volatility that is transferred across markets is known as volatility spillover.

Because of globalization over time, markets across geographic locations and asset classes have become more integrated. Two early studies investigating cross-correlations between markets are Ripley (1973) and Hilliard (1979), who find that there were some diversification benefits due to low correlation between these markets. In 1982, Engle (1982) investigates the means and variances of inflation in the U.K using an autoregressive conditional heteroscedastic model, which is the basis of the ARCH model and the later GARCH (generalized autoregressive conditional heteroscedastic) models. The difference between a traditional econometric model and the ARCH model is that the ARCH model uses a mean zero, serially uncorrelated processes with nonconstant variances conditional on the past, but constant unconditional variances (Engle, 1982). On the other hand, the traditional econometric model assume a constant one-period forecast variance (Engle, 1982). Using the ARCH model presents the possibility to use the recent past to give information about the one-period forecast variance.

Using the work of the Engle (1982, 1988) ARCH-model and the vector autoregressive model (VAR), Diebold and Yilmaz (2009) build a spillover index that allows them to aggregate the spillover effects across markets. With this spillover index, Diebold and Yilmaz can extract a profusion of information contained into a single spillover measure.[3] While the measurement is based on the

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[2] *Further discussion on why this master thesis uses range-based estimator of volatility is presented in the methodology chapter.*

[3] *The spillover index model created by Diebold and Yilmaz will be explained in the methodology chapter*.

ARCH and VAR models of Engle (1982, 1988), the approach by Diebold and Yilmaz is different since their main focus is the variance decomposition.

2.2 Volatility spillover between financial markets

As mentioned above, volatility connectedness between financial markets and financial asset classes is a frequently studied subject. King and Wadhwani (1990) investigate the fact that almost all stock markets fell collectively during the stock market crash in 1987. Moreover, they find that independent markets with little to no relevance with each other seemed to overreact to price movements from other independent markets, a contagion effect. Sakthivel et al. (2012) investigate the correlation and volatility transmission across the international stock markets, and find evidence of bidirectional volatility spillover between the S&P 500 (a US stock index) and BSE 30 sensex (an Indian stock index). The results suggest that these two economies were highly integrated due to international investment and trade. Their results also suggest unidirectional spillover of volatility from the Nikkei 225 (a Japanese stock index) and the FTSE 100 (a U.K stock index) to BSE 30 sensex. Samanta and Zadeh (2012) further extend the scope and examine the co-movements between oil prices, gold prices, the US Dollar, and stocks. They find that the spillover indices in general were very small, but the results indicate that the stock price and gold price were moving more independently than the oil price and exchange rates, which have a greater dependence on other variables.

In this master thesis we us the model of Diebold and Yilmaz (2009, 2012), which is frequently used to understand connectedness both within and between financial markets. In an analysis of 19 global equity markets from 1990 to 2008, Diebold and Yilmaz (2009) study both the return- and volatility spillover, and find evidence that return spillover tends to increase gently but not display any bursts, while the volatility spillover show little evidence of trends but a strong indication of bursts. Later, Diebold and Yilmaz (2012) research the daily volatility spillovers across US stock, bond, foreign exchange, and commodities markets and find that cross-market spillovers were not significant until the global financial crises hit in 2007. After the global financial crises, the volatility spillovers became more substantial, and they find that especially the volatility spillovers from the stock market to the other markets increased. Other studies using the volatility spillover methodology of Diebold and Yilmaz (2009, 2012) are Antonakakis and Kizys (2015), Zhang and Wang (2014), Cronin (2014), Kumar (2013), and Sumner et al. (2010).

2.2.1 Volatility spillover between the cryptocurrency market and other financial markets

The connectedness between cryptocurrencies and other financial assets is also a topic of other studies. Dyhrberg (2016) suggest that Bitcoin has several similarities to Gold and can be used as a medium of exchange for risk averse investors in anticipation of negative shocks to the market. Dyhrberg (2016) explains that Bitcoin is in a position between a pure medium of exchange and a pure store of value, and therefore could be classified as something in between the American dollar and Gold. This is further discussed by Baur et al. (2018), where they replicate Dyhrberg's work and find that empirically Bitcoin is in fact very different from Gold, a stark contrast to Dyhrberg's suggestion.

Bouri et al. (2017) assess the ability of Bitcoin to act as a diversifier, hedge, or a safe haven against daily movements in commodities. They find that Bitcoin could act as both a safe haven and diversifier before the December 2013 Bitcoin price crash. In the post-crash period, Bitcoin only worked as a diversifier. Corbet et al. (2018) brings the analysis one step further by including two more cryptocurrencies, Ripple and Litecoin, and finds that these cryptocurrencies can work as a diversifier for short-term investors.

2.3 Volatility spillover within the cryptocurrency market

Even though connectedness within the cryptocurrency market has received less attention, there are some studies on the topic. By applying a three pair-wise bivariate BEKK-MGARCH model, Katsiampa et al. (2019) investigate the conditional volatility dynamics between three pairs of cryptocurrencies, adjacent to the interlinkages and the conditional correlations. They find evidence of bi-directional spillover effects between all the three pairs of cryptocurrencies, namely Bitcoin-Ether, Bitcoin-Litecoin, and Ether-Litecoin. In terms of time-varying conditional correlations, the results from the test conclude that it exists, and they are in general positive. To differentiate from this paper, we expand on the work of Katsiampa et al. (2019), by testing 9 different currencies and dividing them into Currency, Protocol and dApps.

Both Kumar & Anadarao (2019) and Mighri & Alsaggaf (2019) use GARH models to investigate the dynamics of volatility spillovers in the cryptocurrency market. While Mighri and Alsaggaf focus more on the technical aspect of hedging strategies and optimal portfolio weights, Kumar and Anandarao focus more on the fundamentals behind what causes the volatility and whether there in fact is a statistic significant spillover in the market. In both studies, they conclude that there is in fact a connectedness in terms of volatility spillover in the cryptocurrency market. We utilize this prior information and elaborate on the conclusions in both Kumar & Anadarao (2019) and Mighri & Alsaggaf (2019) by measuring the connectedness within the cryptocurrencies in the sampled dataset.

There are several methods used for calculating volatility spillover. In contrast with the GARCH models used in the aforementioned articles, both Ji et al. (2019) and Yi et al. (2018) use the generalized spillover method developed by Diebold and Yilmaz (2009, 2012). Ji et al. (2019) discovers that return shocks stemming from Litecoin and Bitcoin influences the other cryptocurrencies the most and that Bitcoin, in terms of volatility spillover, are the most influential. They conclude that connectedness via negative returns is generally stronger than via positive ones. Yi et al. (2018) uses eight cryptocurrencies to test for volatility spillover, ranging from small, big, and medium size in terms of market capitalization. The studies indicate that the connectedness in the market varies cyclically and since 2016, has shown an upward trend. They also observe that some unnoticeable cryptocurrencies with significantly smaller market capitalization are net-transmitters of volatility connectedness and contributes largely, in regard to volatility spillovers, to other considerably larger cryptocurrencies (Yi et al., 2018).

3 Cryptocurrency Market

3.1 What is cryptocurrency?

Progressing from a boom in the cryptocurrency market over the last decade, cryptocurrencies have captured the interest of the public. The biggest contrast to traditional currencies is that cryptocurrencies utilized a new payment system based on cryptography, ensuring anonymity, low cost, and fast speed of peer-to-peer transactions (Fisch, 2019). Furthermore, cryptocurrencies are a decentralized digital currency where no bank or government prerequisites control it. Using blockchain technology, which is controlled through a consensus of market participants, helps ensure security. Since cryptocurrencies are managed via decentralized organization, they are not controlled by any one person or entity. Instead, predefined protocols are what determine interactions between classes of individuals involved in the organization. Note that such protocols can still be designed to ensure that certain individuals have more power than others. For instance, depending on the number of shares owned – exactly as with centralized organizations (Infante, 2019).

To further understand what cryptocurrencies are, it is important to understand the underlying technology behind the digital assets. This helps to give an intuition as to why a cryptocurrency has value and how security in cryptocurrency works. Blockchain is a type or subset of distributed ledger technology (DLT), which is used to record and share data across multiple data stores (ledgers). The ledgers contain the exact same data records and collective control through a distribution of computer servers called nodes, which ensures security (Houben & Snyers, 2018). Like blockchain, cryptocurrencies have become a word to refer to a wide array of technological developments that utilize a technique known as cryptography. Cryptography protects information by transforming it into an unreadable format that can only be decrypted by someone who possesses the necessary key. Cryptocurrencies like Bitcoin are secured through this system of public and private digital keys (Houben & Snyers, 2018).

3.2 Research on cryptocurrency

Previous literature on cryptocurrency mainly focus on Bitcoin (Yi et al., 2018). More evidence is seen in Zhang et al. (2018), who focus on three aspects: first, they analyze the inefficiency of Bitcoin, second they investigate the pricing dynamics of Bitcoin and its correlation with other financial assets, and third, they focuses on the long-range dependence of Bitcoin returns. As seen in both these articles mentioned above, and others not discussed, it seems that the primary focus is on Bitcoin.

Furthermore, other articles (e.g. Koutmos, 2018; Yi et al., 2018) dive deeper into the cryptocurrency market, testing the connectedness within the cryptocurrency market. However, although they test the connectedness within cryptocurrencies, they focus on the larger market cap cryptocurrencies. It is, however, crucial to not view all cryptocurrencies as equal since they do not have equal functions. Corbet et al. (2020b) argue that all digital assets should not be viewed as having similar market characteristics. Hence, the importance of differentiating the cryptocurrencies as different assets based on their primary use can be compared to e.g. the importance of distinguishing between treasury bonds and junk bonds. Therefore, to provide further research to the cryptocurrency market and differentiate from previous articles, we also measure the interdependencies within selected categories.

3.3 Classification of cryptocurrencies

Since the primary use of cryptocurrencies differs, a general classification of the main uses seems logical to provide better insight to the relations and how they generate value. Corbet et al. (2020b) has classified digital assets into three categories based on their primary use:

1. Currencies: The primary use of Currencies is money transfer and financial payments, and most often that is also their sole purpose. The most notable, and used, digital asset is Bitcoin. It is a peer-to-peer digital asset, which is decentralized, meaning it is not influenced by any monetary authority. Currencies developed later aim to improve on aspects where their

predecessors lacked robustness. Overall cryptocurrencies created with the intention of being used for financial payments or monetary transfer are classified as a Currency (Corbet et al., 2020b). Their value does not only come because of their role and use, Currencies have a network distributing a fixed amount of ‘coins’. Bitcoin can never exceed 21 million coins, wheras Litecoin, for example, can lodge up to 84 million coins (Fernando, 2019).

2. Protocols: The main use of Protocols is the blockchain platform (protocol), which is the technology used. Other decentralized applications can be built on the protocol. Protocols are digital assets with the primary function of transferring data and providing a platform to build decentralized applications on. Consequently, unlike Currencies, Protocols are not a medium of exchange or value transferring, but rather focuses on data transfer and technology as a platform. The Protocols derive their value from the usage of their platform. The value can come from dApps built on the protocol and subsequently using the protocol’s currency as a medium of exchange (Corbet et al., 2020b).

3. Decentralized Applications (dApps): Applications that combine a decentralized back end and a user interface. They are built upon a Protocol’s blockchain. The way these dApps differ as a digital asset is that they have front-end code for their interface but use the back-end code of a preexisting protocol. Examples of blockchain dApps are decentralized storage applications (Corbet et al., 2020b).

3.4 Selected cryptocurrencies

There are two main considerations we consider in selecting the nine cryptocurrencies for this thesis. The first consideration is that all the chosen cryptocurrencies must have enough historical data for a robust analysis. The second consideration is for each category to have at least one high-, medium-, and low market capitalization cryptocurrency. All categories were intended to have one of each, where the cryptocurrencies for high-, medium, and low respectively were of approximately equal rank. However, because the dApps cryptocurrencies are a new branch of cryptocurrency built upon a Protocol, they had less data and lower market capitalizations. Therefore, to avoid compromising the dataset, the implication resulted in no large capitalization dApp around the same rank as for those from the Currency and Protocol. Another limitation is that only the Ethereum protocol had dApps that had substantial data for the analysis. Further research should analyze the connectedness between dApps and the Protocols that those respective dApps are built upon.

Based on these considerations, we chose the following cryptocurrencies:

Table 1: Table for the selected cryptocurrencies.

	Average Market Capitalization		
	High	**Medium**	**Low**
Currency	Litecoin	Monacoin	Counterparty
Protocol	Ethereum	Waves	LBRY Credits
dApp	Golem	Digixdao	Singular DTV

4 Methodology

4.1 Time Series Analysis

Time series models are a class of specifications that consists of observations of one, or numerous variables over a predetermined period (Brooks, 2014). A distinct feature that separates it from structural models is that it predicts financial variables only using information included in their own past values and in some cases information of current and past values of the error term. The data used can vary in frequency based on what is most appropriate for the dataset, i.e. daily, weekly, monthly, or yearly. More information of the basics behind time series regression, the autoregression model, the moving average model and descriptive statistical tests can be found in Brooks (2014) and Wooldridge (2016).

4.2 Forecast Error Variance Decomposition

Before explaining the method of Diebold and Yilmaz (2009) to identify volatility spillover, it is necessary to define the term forecast error variance decomposition (FEVD). FEVD is a tool to interpret VAR models (Lütkepohl, 2005). It gives the fraction of the movements in the dependent variable that are due to their own shocks compared to shocks to the other variables (Brooks, 2014). Denoting H as the number of steps ahead, the FEVD will identify the proportion of the H-step ahead error variance when forecasting one variable is due to another variable.

4.3 Diebold & Yilmaz volatility spillover index

Measuring connectedness between markets is a concept explored by many researchers. The method of measuring connectedness proposed by Diebold and Yilmaz (2009, 2012) takes a spillover index into account. Focusing on variance decompositions, it allows for aggregate spillover effects across markets, distilling a wealth of information into a single spillover measure (Diebold & Yilmaz, 2009, 2012). There is, however, a limitation. The spillover index provides a useful summary of average “behavior”, but it is likely to miss potential secular and cyclical movements in spillovers. Addressing the issue, they propose using rolling samples. Rolling samples can be adjusted for appropriate windows of example

100-days, 200-days, etc. This method helps assess the extent of variation in spillover over time via the matching time series of spillover indexes (Diebold & Yilmaz, 2009, 2012). Because the dataset is limited regarding datapoints, the primary focus will be on the generalized spillover index. Using rolling samples, it is possible to test the robustness of the spillover index and identify some periods with significantly higher volatility than others.

4.3.1 Volatility Spillover

The idea behind the volatility spillover index developed in Yilmaz and Diebold (2009) is to decompose the variance, which allows them to identify spillover effects between markets and summarize them in a spillover index. As an example, consider a bivariate VAR(1) model ($Y_{1,t}$,$Y_{2,t}$) corresponding with an error vector:

$$e_{t+1,t} = y_{t+1} - \hat{y}_{t+1,t} = A_0 u_{t+1} = \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} u_{1,t+1} \\ u_{2,t+1} \end{pmatrix} \quad (4.1)$$

With a corresponding matrix

$$E(e_{t+1,t} e'_{t+1,t}) = A_0 A'_0 \text{ (Diebold \& Yilmaz, 2009)} \quad (4.2)$$

By studying equation (4.1), we see that the variance of the 1-step ahead error in forecasting y_{1t} is $a_{0,11}^2 + a_{0,12}^2$ while for y_{2t}, the variance of the 1-step ahead error in forecasting is $a_{0,21}^2 + a_{0,22}^2$. There exists two possible spillovers in the bivariate VAR(1) model presented: shocks from y_{1t} that influences the forecast error variance y_{2t} by contribution to $a_{0,21}^2$, and shocks from y_{2t} that influences y_{1t} with contribution to $a_{0,12}^2$. The total spillover here will then be the sum of the contributions, hence $a_{0,21}^2 + a_{0,12}^2$. Diebold and Yilmaz (2009) define the volatility spillover index, as the ratio between the relative and the total forecast error variation:

$$Spillover\ Index = \frac{a_{0,21}^2 + a_{0,12}^2}{a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2} \times 100 = \frac{a_{0,21}^2 + a_{0,12}^2}{trace\ (A_0 A'_0)} \quad (4.3)$$

In the general case of a N-variable VAR of a pth order using H-step ahead forecast, Diebold and Yilmaz (2009) express it as:

$$Spillover\ Index = \frac{\sum_{s=0}^{S-1}\sum_{i,j=1,i\neq j}^{N} a_{s,ij}^2}{\sum_{s=0}^{S-1} trace(A_s A'_s)} \tag{4.4}$$

Here, the nominator represents the contributions, while the denominator represents the sum of all elements.

4.3.2 Generalized Spillover Index

The spillover index of Diebold and Yilmaz (2009) is dependent of the order of the variables. In an extension of the spillover index, Diebold and Yilmaz (2012) proposed a generalized version that allows for identification of directional spillovers, net spillovers, and net pairwise spillovers. By using the generalized VAR framework developed in Pesaran and Shin (1998) and Koop et al (1996) (hereafter KPPS) rather than the Cholesky factorization they used in their 2009 version of the index to obtain the FEVD, they are able to capture these effects in a non-order dependent framework.

4.3.2.1 Deriving the Generalize Spillover Index

The first step of deriving the generalized spillover index is to consider a covariance stationary N-variable VAR(p),

$$Y_t = v + \sum_{i=1}^{p} \Phi_i Y_{t-1} + \varepsilon_t \tag{4.5}$$

Here Y_t represents an N × 1 vector of dependent variables. Further, v represents the intercept terms through an N × 1 vector, while Φ_i represents the autoregressive coefficients in the form of an N × N matrices. The error term ε_t is an N × 1 vector. It is assumed that the error terms are independently and identically distributed disturbances with expectation zero and covariance matrix Σ, ε ~ (0, Σ). A moving average representation of equation (4.5) is necessary to obtain the FEVD:

$$Y_t = \mu + \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{4.6}$$

where the N×N coefficient matrices A_i follows the recursion

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}, \qquad (4.7)$$

where A_0 is an N×N identity matrix and $A_i = 0$ for i < 0. The key to understanding the dynamics of this system is via the moving average coefficients presented above (Diebold & Yilmaz, 2012). The MA coefficients enables us to identify the FEVD of each variable and separate them into parts. In return, we can identify the directional spillover through shocks to the system. In other words, the variance decomposition presents the possibility to assess the fraction of the H-step-ahead error variance in forecasting y_i that comes from shocks to y_j for all j =1,2,…,N (Diebold & Yilmaz, 2012).

4.3.2.2 Intuition behind the forecast error variance decomposition

Diebold and Yilmaz (2012) define the fractions of the H-step-ahead error variance in forecasting y_i that are due to shocks to y_i for all N variables as *own variance shares,* while the fractions of H-step-ahead error variance in forecasting y_i that are due to shocks to y_j for all N-variables is defined as *cross-variance shares*, also known as spillovers. Defining the KPPS H-step-ahead forecast error variance decomposition as $\theta_{ij}^{g}(H)$ for H = 1,2…, we get

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_i)} \qquad (4.8)$$

where Σ is the variance matrix for the error term vector ε_t, e_i is a selection vector where the *i*th element is set to one and all other elements set to zero, and the standard deviation of the error term for the *j*th equation is represented by σ_{jj}.

The main difference between the KPPS method and the Cholesky factorization is that the KPPS method is invariant to the ordering of the variables. Where the Cholesky factorization achieve orthogonality, the KPPS method allows for correlated shocks but accounts for them appropriately using the historically distribution of the errors (Diebold & Yilmaz, 2012). As a consequence of not achieving orthogonality in the shocks to each variable, the row sum of the contribution to the variance of the forecast error may not equal to one. Diebold and Yilmaz (2012) proposed a solution by normalizing each entry θ_{ij}^{g} by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{4.9}$$

Normalizing each element by substituting it with the output from equation (4.9) forces the row sum to equal one.

4.3.2.3 Total spillover index

The total volatility spillover index is then structured using the volatility contributions from the KPPS variance decomposition.

$$S^{g}(H) = \frac{\sum_{\substack{i,\ j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,\ j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{4.10}$$

By dividing the off-diagonal elements from the normalized forecast error variance decomposition table resulting from equation (4.8) by the sum of all table elements, the generalized spillover index is obtained. Equation (4.10) presents the KPPS analog of the Cholesky factor-based measure derived in subchapter 4.3.1. Thus, the total spillover index represents in more general terms the contribution of spillovers of volatility shock when compared to the total forecast error variance.

4.3.2.4 Directional- and net spillovers

With the generalized spillover method developed in Diebold and Yilmaz (2009, 2012) we are not only able to identify the total spillover, but also the direction of the volatility spillovers across markets. This is one of the most significant advantages with this model compared to other volatility spillover models. Using the normalized elements of the generalized variance decomposition matrix, we can identify the directional spillover received by market *i* from all other markets *j* as:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{i,\ j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,\ j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{4.11}$$

Here, the row sum of cross-variance shares for market *i* is divided by the sum of all FEVD normalized elements. Equation (4.11) explains the volatility spillover received by market *i*. In the same manner as equation (4.11), the volatility spillover received by market *j* from market *i* can be calculated as:

$$S_{.i}^{g}(H) = \frac{\sum_{i,\ j=1,\ i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,\ j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 \qquad (4.12)$$

In more general terms, the directional spillovers are the decomposition of the total spillovers coming from a market or received by another (Diebold & Yilmaz, 2012). The net spillover is calculated by taking the difference between the gross volatility transmitted to all other markets *j* from market *i* and the gross volatility received from all other markets *j* to market *i*:

$$S_{i}^{g}(H) = S_{i.}^{g}(H) - S_{.i}^{g}(H) \qquad (4.13)$$

4.3.2.5 Net pairwise spillovers

As explained above, the net spillover yields information about how much volatility spillover is transmitted (received) from (by) one market to (from) all other markets. When working with several different markets, let us say *k* markets, it could be of special interest to study the direct relationship between market *i* and *j* separately. The net pairwise spillover is defined by Diebold and Yilmaz (2012) as the difference between gross volatility spillover transmitted by market *i* to market *j* and the gross volatility spillover transmitted by market *j to* market *i*. The net pairwise spillovers is calculated in equation (4.14) as:

$$S_{i.}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,\ k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,\ k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) \times 100 \qquad (4.14)$$

4.4 Volatility Estimator

As mentioned in the literature review, the volatility estimator is a deeply researched subject within economic and finance. Molnàr (2012) discusses the importance of a precise volatility estimator and systematically analyze different estimators of volatility, their advantages, and their disadvantages. In particular, he studies the variance estimator, the squared returns estimator, and the range-based estimator. His conclusion is that the Garman-Klass (1980) range-based estimator of volatility is the most precise estimator of volatility and that this estimator delivers a significant increase in accuracy when compared to squared returns. This is also the same estimator of volatility used in Diebold & Yilmaz(2009, 2012). The Garman-Klass (1980) estimator is presented below:

$$\hat{\sigma}^2 = 0.511(H_t - L_t)^2 - 0.019(C_t - O_t)(H_t + L_t - 2O_t) \quad (4.15)$$

$$-2(H_t - O_t)(L_t - O_t) - 0.383(C_t - O_t)^2$$

Here the C is the daily closing price, O is the daily opening price, H is the daily high, and L is the daily low. Further explanation can be found in Garman and Klass (1980) and Molnàr (Molnár, 2012). We use this estimator as our primary estimator of volatility throughout the thesis.

5 Data

The primary data in this thesis are daily open, close, low, and high prices for a set of 9 different cryptocurrencies from November 2016 to June 2020. We have a total of 1292 observations per cryptocurrency. However, due to the circumstances around COVID-19, we separate the data into two parts. The first dataset consists of prices ranging from 18.11.2016 to 28.02.2020, while the second dataset adds the COVID-19 dates and gives a data sample until 01.06.2020. Further, cryptocurrencies do not have specific trading days, meaning trading days for cryptocurrencies are all calendar days. However, because we also test these cryptocurrencies against both the S&P and other commodities, non-trading days are omitted to match the comparison across markets. After applying these filters, we have between 824 and 887 observations per cryptocurrency. Indicating that e.g. the weekend data for cryptocurrencies are omitted and therefore, the typical following trading day of a Friday, will be a Monday. The cryptocurrency data is extracted from Coinmarketcap.com, while the other indices are extracted from investing.com. Moreover, there are no data gaps within the timeframe for all price series, resulting in no exclusion of data due to lack of data on independent days.

In our thesis, we create two indices for the cryptocurrencies. These indices are a proxy for the overall volatility from the nine cryptocurrencies. The value weighted index (VWI) is an index based on the market capitalization of the different currencies. VWI is created using one day lagged daily market capitalization to calculate the individual weights for the cryptocurrencies. Recalculating the market capitalization each day enables us to capture big movements in market capitalization, which reflects the daily weights. This means cryptocurrencies with higher market capitalization have a larger weight in the VWI. The weights in the VWI are weights for the daily volatility of each cryptocurrency within the index. Note, given the focus of this thesis on volatility, the index does not use returns. Instead, we use the weighted volatilities, and thus are not incorporating any form of diversification effects in the first moment. Instead, we use the index as a simple proxy for the overall volatility among these nine cryptocurrencies. In addition, we generate an equally weighted index (EWI) that gives equal weights to all selected cryptocurrencies. This is to be sure any observed effects are not solely due to the larger market capitalization cryptocurrencies, and instead better reflects the volatility of the smaller cryptocurrencies.

From Table 2 it is apparent that the daily volatilities for the cryptocurrencies are within a broad range. The mathematical properties of volatility calculation result in no negative values. It is evident from Table 2 that lower cap cryptocurrencies have more extreme daily volatilities and higher daily volatility on average. This might be due to possible market manipulation for low cap cryptocurrencies.

Table 2: Descriptive statistics of daily volatility (in %) without COVID-19 dates. For all cryptocurrencies.

	Min	Max	Median	Mean	Std.dev	Kurtosis	Skewness
EWI Currency	0,010	17,125	0,323	0,757	1,414	52,634	5,834
Litecoin	0,002	13,131	0,129	0,340	0,835	100,603	8,425
Monacoin	0,000	49,268	0,240	0,850	2,550	171,608	10,658
Counterparty	0,000	49,640	0,396	1,079	2,623	153,009	9,719
EWI Protocol	0,025	10,665	0,394	0,680	0,966	29,810	4,309
Ethereum	0,004	7,354	0,104	0,299	0,674	50,093	6,154
Waves	0,005	10,770	0,252	0,537	0,937	43,411	5,309
LBRY Credits	0,021	21,866	0,583	1,205	1,992	33,174	4,691
EWI dApps	0,031	17,549	0,494	0,930	1,559	52,496	6,038
Digixdao	0,010	49,985	0,262	0,724	2,180	326,488	15,522
Golem	0,007	46,564	0,350	0,887	2,158	253,057	13,092
Singular DTV	0,020	52,448	0,456	1,168	2,750	165,508	10,458

Table 3 updates Table 2 to include the COVID-19 period. Comparing it to Table 2, the inclusion of COVID-19 in the dataset does not affect the range of daily volatilities substantially.

Table 3: Descriptive statistics of daily volatility (in %) with COVID-19 dates. For all cryptocurrencies.

	Min	Max	Median	Mean	Std.dev	Kurtosis	Skewness
EWI Currency	0,010	17,125	0,309	0,733	1,379	54,530	5,918
Litecoin	0,002	13,131	0,129	0,343	0,851	93,372	8,183
Monacoin	0,000	49,268	0,220	0,814	2,470	181,318	10,925
Counterparty	0,000	49,640	0,392	1,044	2,549	159,916	9,893
EWI Protocol	0,025	10,665	0,381	0,688	1,004	28,835	4,317
Ethereum	0,004	7,354	0,103	0,301	0,691	47,190	6,026
Waves	0,002	10,770	0,242	0,538	0,972	43,034	5,361
LBRY Credits	0,021	21,866	0,583	1,224	2,043	30,630	4,559
EWI dApps	0,031	17,549	0,488	0,927	1,559	50,345	5,902
Digixdao	0,010	49,985	0,246	0,714	2,120	338,865	15,704
Golem	0,007	46,564	0,335	0,874	2,113	256,010	13,042
Singular DTV	0,020	52,448	0,456	1,193	2,750	154,295	9,936

Table 4 provides a summary of the descriptive statistics for the daily volatility series of included indices. The data consists of the trading days of the S&P 500 throughout the sampled period but excludes COVID-19 dates. From Table 4 non-cryptocurrency indices have a lower range of daily volatility and lower average daily volatility. Furthermore, the EWI has a higher average daily volatility than the VWI and has a larger standard deviation. Since the VWI weights the cryptocurrencies while the EWI does not, lower cap cryptocurrencies have a larger weight in the EWI.

Table 4: Descriptive statistics of daily volatility (in %) without COVID-19 dates. For all indexes.

	Min	**Max**	**Median**	**Mean**	**Std.dev**	**Kurtosis**	**Skewness**
S&P 500	0,000	0,083	0,002	0,004	0,008	33,934	5,007
Gold	0,000	0,087	0,004	0,005	0,006	76,073	6,750
Copper	0,002	0,366	0,016	0,023	0,025	55,001	5,318
EWI	0,049	12,035	0,490	0,789	1,020	32,298	4,414
VWI	0,000	8,515	0,126	0,320	0,675	56,665	6,434

Table 5 has an overview of the descriptive statistics for the daily volatility series of the S&P 500 and Gold. Compared to Table 4, the data sample now includes COVID-19. The result of COVID-19 in the data sample is a much larger maximum daily volatility for the S&P 500 and Gold. Further, the mean and standard deviation have increased slightly. The COVID-19 days represent less than 10% of the full sample and therefore, the effect will be limited. Overall, Table 4 reflects that a crisis seems to increase the volatility relative to normal times.

Table 5: Descriptive statistics of daily volatility (in %) with COVID-19 dates. For S&P 500 and Gold.

	Min	**Max**	**Median**	**Mean**	**Std.dev**	**Kurtosis**	**Skewness**
S&P 500	0,000	0,260	0,002	0,007	0,021	74,313	7,708
Gold	0,000	0,306	0,004	0,007	0,015	196,612	11,867

Table 6 provides a summary of the descriptive statistical tests for the daily volatility series not including COVID-19 in the sample period. Explanation for these tests can be found in Brooks (2014) and Woldridge (2016). In the Jarque Bera test, we reject the null of normality for all series. The Portmanteau test for white noise, rejects the null of zero autocorrelation. Furthermore, two stationarity tests were conducted, Augmented Dickey Fuller and Phillips-Perron. Both concluding that the series of daily volatility are stationary. All tests are statistically significant at the 0,01% level. The overall implications are that the series of daily volatility are non-normally distributed, have autocorrelation, and are stationary.

Table 6: Descriptive statistical tests for the daily volatilities without COVID-19 dates. For all cryptocurrencies.

	JB	PM	ADF	PP
EWICurr	-	99,43	-14,10	-19,76
Litecoin	-	90,64	-15,50	-20,22
Monacoin	-	53,83	-16,41	-22,01
Counterparty	-	52,19	-15,07	-22,05
EWIProt	-	168,07	-12,45	-17,27
Ethereum	-	129,05	-14,60	-18,74
Waves	-	81,28	-14,27	-20,13
LBRY Credits	-	121,45	-13,53	-18,91
EWIdApps	-	59,54	-14,79	-21,60
Digixdao	-	27,46	-17,53	-23,80
Golem	-	29,50	-16,68	-23,49
Singular DTV	-	16,12	-17,09	-24,86

Table 7 provides a summary of the descriptive statistical tests for the daily volatility series including COVID-19 in the data sample. Consistent with the Table 6, all tests are statistically significant at the 0,01% level. The overall implications are that COVID-19 does not affect the normality, autocorrelation, or stationarity of the datasets.

Table 7: Descriptive statistical tests for the daily volatilities with COVID-19 dates. For all cryptocurrencies.

	JB	PM	ADF	PP
EWICurr	-	108,48	-14,68	-20,47
Litecoin	-	100,93	-16,37	-20,89
Monacoin	-	59,37	-17,00	-22,78
Counterparty	-	57,87	-15,63	-22,80
EWIProt	-	191,53	-13,41	-17,72
Ethereum	-	150,86	-15,54	-19,13
Waves	-	92,85	-14,95	-20,75
LBRY Credits	-	131,60	-14,42	-19,64
EWIdApps	-	71,38	-15,45	-22,08
Digixdao	-	31,92	-18,19	-24,53
Golem	-	36,66	-17,21	-24,03
Singular DTV	-	20,99	-17,83	-25,44

Table 8 provides a summary of the descriptive statistical tests for the daily volatility series for the indexes, not including COVID-19. Like the cryptocurrencies tested, the indexes are all statistically significant at the 0,01% level. The conclusion of these tests is that all indexes are non-normal, have autocorrelation and are stationary.

Table 8: Descriptive statistical tests for the daily volatilities without COVID-19 dates. For all indexes.

	JB	PM	ADF	PP
S&P 500	-	257,66	-11,71	-15,34
Gold	-	32,26	-16,98	-27,10
Copper	-	72,92	-15,65	-21,05
EWI	-	147,03	-12,59	-17,93
VWI	-	129,32	-14,55	-18,72

Table 9 provides a summary of the descriptive statistical tests for the daily volatility series for the S&P 500 and Gold, including COVID-19. Both indexes are statistically significant at the 0,01% level, concluding that they are non-normal, have autocorrelation and are stationary.

Table 9: Descriptive statistical tests for the daily volatilities with COVID-19 dates. For S&P500 and Gold.

	JB	PM	ADF	PP
S&P 500	-	533,76	-6,64	-9,30
Gold	-	444,67	-10,52	-12,19

6 Empirical Results

This chapter presents the findings from utilizing the generalized spillover index of Diebold and Yilmaz (2009, 2012). We use the generalized spillover index to investigate both the cryptocurrency market, and how the cryptocurrency market moves relative to other financial markets before and during the COVID-19 pandemic. The analysis is divided into three parts and we will perform both a full-sample analysis and a rolling window analysis of the volatility spillover for the latter two parts of the analysis. The first part will consist of only a full-sample analysis.

The first part of the analysis investigates how, in terms of volatility, a value weighted index and an equally weighted index consisting of nine selected cryptocurrencies move with S&P 500 and Gold. Moreover, to analyze the role of market capitalization, the commodity Copper is included. The next part of the analysis dives into the volatility spillover within the cryptocurrency market by looking at how the nine different cryptocurrencies move with each other. An important part of the thesis is the fact that the cryptocurrency market can be divided into three asset classes based on their primary use. Following this, the next part of the analysis examines the relationship between these asset classes. The last part of the chapter explores how the cryptocurrency market behaves before and during the initial phase of the COVID-19 pandemic, as well as looking at how the cryptocurrency market is affected by a crisis compared to S&P 500 and Gold (8,9).

To perform the full-sample and rolling-window spillover analysis, a covariance stationary N-variable VAR(p) model is required. As implied, the model requires stationarity which is tested for and presented in Table 5 and 7. The variables included in the analysis presented above are the daily volatilities calculated by the Garman-Klass (1980) estimator, where each variable in each analysis correspond to the daily volatilities. As an example, the first analysis includes three variables represented by the daily volatilities of VWI, Gold and S&P 500.

The number of lags included in the VAR(p) model for each analysis is determined by minimizing the information criteria SC, AIC, HQ and FPE.[4] The number of lags has been set to maximum 10, and the results are presented in Table 10. In conjunction with the parsimonious principle, the number of lags has been set to 1 in the VAR(p) for each analysis. The reason behind this is that the values from the information criteria presents marginal difference for lags of 1 and 10.

Table 10: Displayed below is the values of the information criteria's AIC, HQ, SC and FPE for all analyses.

Analysis	**(1)**		**(2)**		**(3)**		**(4)**	
Lags	1	10	1	10	1	10	1	10
AIC	-49,3	-49,4	-48,5	-48,7	-56,0	-56,1	-76,2	-75,9
HQ	-49,3	-49,2	-48,5	-48,5	-55,9	-55,9	-76,0	-74,5
SC	-49,2	-48,9	-48,4	-48,2	-55,9	-55,6	-75,8	-72,4
FPE	0,0	0,0	0,0	0,0	0,0	0,0	0,0	45,0

Analysis	**(5)**		**(6)**		**(7)**		**(8)**		**(9)**	
Lags	1	10	1	10	1	10	1	10	1	
AIC	-26,5	-26,5	-76,4	-76,1	-26,5	-26,5	-46,6	-47,3	-45,8	-46,5
HQ	-26,5	-26,4	-76,3	-74,9	-26,5	-26,4	-46,6	-47,1	-45,8	-46,3
SC	-26,4	-26,1	-76,1	-72,8	-26,4	-26,2	-46,6	-46,8	-45,8	-46,0
FPE	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0

The H-step predictor described in the methodology is set to 10, which is the same as two business weeks. When testing the data, the FEVD table stayed unchanged when the H-step predictor was equal to 10 and as mentioned in the methodology chapter, the H-step predictor should be set high enough that a unit increase in H-step predictor shall not affect the elements of the FEVD table.

6.1 Analysis of Cryptocurrency market, S&P 500, and Gold.

The first part of the analysis presents empirical results from three separate analysis conducted on how an index of nine different cryptocurrencies behaves in

[4] *More information about the information criteria's can be found in Brooks (2014) and Wooldridge (2016).*

terms of volatility when tested against the gold market and S&P 500. The first analysis is between a value weighted index (VWI) and an equally weighted index (EWI) of the nine cryptocurrencies, Gold, and S&P 500. The final analysis is between Copper, Gold, and S&P 500. This is performed with the full-sample volatility spillover analysis.

6.1.1 Full-Sample Analysis of Volatility spillover

We present the results of the full-sample analysis of the volatility spillover between EWI, VWI, S&P 500 and Gold, in Table 11 and Table 12. Known as a volatility spillover table, it summarizes all the spillover (total, directional, and net) and includes the normalized FEVD table which was explained in the methodology chapter. In the table, the diagonal elements represent their own variance shares, while the off-diagonal represents the cross-variance shares. Because the FEVD is normalized, as explained in subchapter 4.3.2.2, the sum of each row is equal to 100%. The "directional to others" explain the aggregated volatility transferred to all other markets *j* from market *i* while "directional from others" explain the aggregated volatility received from all other markets *j* to market *i*.

Table 11: Volatility spillover table for the indexes (VWI, S&P500 and Gold) without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	S&P 500	**Gold**	**VWI**	**Directional FROM others**
S&P 500	**98,562**	1,308	0,130	1,438
Gold	1,391	**98,570**	0,038	1,430
VWI	0,458	0,112	**99,430**	0,570
				Total spillover index:
Directional TO others	1,849	1,421	0,168	1,146 %
Directional including own	100,411	99,991	99,598	
Net spillover	0,411	-0,009	-0,402	

From Table 11, total spillover between the market's accounts for 1,146% of the volatility in the markets included in the analysis, implying a weak connectedness between the markets. Looking at the diagonal elements of the table, the numbers imply that most of the volatility comes from within its own market. The S&P 500 and Gold both affect each other's volatility by a small percentage[5], however, their behavior towards and from the VWI is very low. This is consistent with the findings of Ji et al. (2019), who report strong interdependence within the cryptocurrency market, and it is consistent with the findings of Corbet et al. (2018) who conclude that cryptocurrencies are fairly isolated from both S&P 500 and Gold. Overall, the S&P 500 is a net transmitter, while Gold and VWI are net receivers.

Since the market capitalization differences between the nine used cryptocurrencies are high, the representation of the volatility of the larger cryptocurrencies in the VWI gives the lower capitalized cryptocurrencies an insubstantial representation in this index. Therefore, to equally represent the volatility of the nine cryptocurrencies, we generate an equally weighted index. The full-sample volatility spillover table with EWI is presented below.

Table 12: Volatility spillover table for the indexes (EWI, S&P500 and Gold) without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	S&P 500	**Gold**	**EWI**	**Directional FROM others**
S&P 500	**98,427**	1,334	0,239	1,573
Gold	1,402	**98,459**	0,138	1,541
EWI	0,088	0,223	**99,688**	0,312
				Total spillover index:
Directional TO others	1,491	1,557	0,377	1,142 %
Directional including own	99,918	100,017	100,065	
Net spillover	-0,082	0,017	0,065	

As seen from Table 12, the change in volatility spillover towards and from the cryptocurrency market, as well as the total spillover, do not change substantially and the results still show that most of the volatility in the cryptocurrency market comes from within the market itself.

[5] *The dataset is represented of daily volatilities from 18.11.2016 until 28.02.2020. So, this may not reflect the entirety of the connectedness between S&P 500 and Gold. This test is primarily to see the connectedness between these two financial markets and the cryptocurrency market during the available time-period for the cryptocurrencies.*

6.1.1.1 Copper

The cryptocurrency market is a young market and has a relatively low market capitalization compared to S&P 500 and Gold. To test that the volatility within the cryptocurrency market may not be explained by its low market capitalization, but rather because of volatility within the cryptocurrency market itself, we have included the commodity Copper. The total market capitalization of EWI/VWI is of similar size[6] as Copper and is therefore a good market to test this hypothesis. The full-sample volatility spillover table with Copper is presented below.

Table 13: Volatility spillover table for the indexes (Copper, S&P500 and Gold) without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	S&P 500	**Gold**	**Copper**	**Directional FROM others**
S&P 500	**92,265**	1,194	6,541	0,036
Gold	1,359	**98,154**	0,487	2,945
Copper	13,098	0,640	**86,262**	0,019
				Total spillover index:
Directional TO others	14,457	1,834	7,028	7,773 %
Directional including own	106,722	99,988	93,290	
Net spillover	6,722	-0,012	-6,710	

In contrast to the previous analysis, it is evident from Table 13 that the total spillover is higher, now being 7,773%. Furthermore, from the sampled period, less of the volatility of Copper comes from within the market itself compared to the EWI/VWI. This supports the hypothesis that the market capitalization may not be the driver of low spillover received from and transferred to S&P 500 and Gold, but that the volatility comes from within the cryptocurrency market itself.

As seen from the analysis above, the results indicate that connectedness between the cryptocurrency market and other financial markets is weak. Further, the results show that that this weak connectedness is unlikely to be driven by the size of the market capitalization. As the results indicate that most of the volatility stems from

[6] *The aggregated market capitalization of the nine cryptocurrencies is 29 billion USD, while the market capitalization of the Southern Copper Market is approximately 26 billion USD, as of 28.02.2020.*

within the cryptocurrency market itself, the next part of the analysis investigates the volatility spillover between the nine selected cryptocurrencies.

6.2 Analysis of Cryptocurrency market

We now examine the volatility spillover among the nine different cryptocurrencies. The selected cryptocurrencies used in the analysis are Litecoin, Monacoin, Counterparty, Ethereum, Waves, LBRY Credits, Dixigdao, Golem, and Singular DTV. We include these cryptocurrencies because they cover the three categories presented in the Cryptocurrency Market chapter. They are also variations of high-, medium-, and low market capitalization cryptocurrencies and these cryptocurrencies are the ones with adequate daily data to make justifiable conclusions. The analysis is performed both with a full-sample and a rolling-window analysis.

6.2.1 Full-Sample Analysis of Volatility spillover

The previous subchapter suggested that most of the volatility in the cryptocurrency market comes from within the market. Therefore, to further explore the volatility in the cryptocurrency market, we conduct an analysis of the interconnectedness within the cryptocurrency market. We present the full-sample analysis of volatility spillover between the nine cryptocurrencies in Table 14.

Table 14: Volatility spillover table for all cryptocurrencies without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	Litecoin	Monacoin	Counterparty	Ethereum	Waves	BRYCredits	Digixdao	Golem	Singular DTV	Directional FROM others
Litecoin	**49,082**	2,732	0,519	19,762	13,867	4,680	3,051	3,966	2,341	50,918
Monacoin	6,325	**77,749**	1,367	3,682	4,172	3,252	1,343	1,144	0,967	22,251
Counterparty	1,312	0,631	**95,144**	1,111	0,915	0,542	0,129	0,139	0,077	4,856
Ethereum	18,470	2,156	0,522	**49,667**	11,998	4,886	3,931	5,775	2,596	50,333
Waves	14,397	1,941	0,748	12,655	**56,828**	5,125	1,642	4,423	2,241	43,172
LBRYCredits	9,247	3,277	0,694	8,217	8,340	**63,659**	1,666	3,556	1,345	36,341
Digixdao	5,397	2,617	0,345	7,621	4,049	2,191	**74,816**	2,261	0,703	25,184
Golem	6,347	0,883	0,106	11,456	6,192	3,353	1,201	**69,229**	1,234	30,771
Singular DTV	4,875	0,860	0,068	4,989	4,398	1,472	0,812	1,430	**81,096**	18,904
										Total spillover index:
Directional TO others	66,370	15,098	4,367	69,493	53,930	25,501	13,774	22,693	11,505	31,414 %
Directional including own	115,842	92,955	99,693	113,214	108,642	89,316	89,164	99,260	91,915	
Net spillover	15,452	-7,153	-0,488	19,160	10,757	-10,840	-11,410	-8,078	-7,399	

As suspected, the total volatility spillover is higher within these nine cryptocurrencies than the total volatility spillover between the markets. The nine cryptocurrencies have an average total spillover of 31,414%, suggesting that

31,414% of the volatility in all nine cryptocurrencies stem from spillover effects in the sample. The spillover table indicates that the own variance shares are still the main provider to the volatility in each cryptocurrency.

We find that there appears to be a relationship between market capitalization and the volatility connectedness of the cryptocurrencies. The two largest cryptocurrencies based on average market capitalization are Ethereum and Litecoin. Both depend more on the volatility of the other cryptocurrencies than their own volatility, which implies a strong volatility connectedness with the other tested cryptocurrencies. This is in line with the findings in Ji et al. (2019c) where they find that Litecoin depends less on its own volatility than the others that were used in the sample. Adding to this, two of the small capitalization cryptocurrencies, Counterparty (Currency) and Singular DTV (dApps), seem to have a weaker volatility connectedness with the other cryptocurrencies.

Furthermore, the three cryptocurrencies with the highest average market capitalization within each category, Litecoin (Currency), Ethereum (Protocol), and Golem (dApps), receive the most volatility spillover from the other cryptocurrencies in the sample. Moreover, the three cryptocurrencies with the lowest average market capitalization within each category, Counterparty (Currency), LBRY Credits (Protocol), and Singular DTV (dApps), receive the least amount of volatility spillover from the other cryptocurrencies in the sample.

To further investigate the directional spillover between the cryptocurrencies, we present a net pairwise table in Table 15.

Table 15: Net pairwise spillover table for all cryptocurrencies without COVID-19 dates.

Net pairwise spillover									
	Litecoin	**Monacoin**	**Counterparty**	**Ethereum**	**Waves**	**LBRYCredits**	**Digixdao**	**Golem**	**Singular DTV**
Litecoin	**0,000**	-3,592	-0,793	1,291	-0,530	-4,567	-2,346	-2,381	-2,534
Monacoin	3,592	**0,000**	0,736	1,526	2,231	-0,025	-1,275	0,261	0,107
Counterparty	0,793	-0,736	**0,000**	0,590	0,167	-0,152	-0,216	-0,034	0,008
Ethereum	-1,291	-1,526	-0,590	**0,000**	-0,657	-3,331	-3,690	-5,681	-2,393
Waves	0,530	-2,231	-0,167	0,657	**0,000**	-3,215	-2,407	-1,769	-2,157
LBRYCredits	4,567	0,025	0,152	3,331	3,215	**0,000**	-0,525	0,203	-0,127
Digixdao DTV	2,346	1,275	0,216	3,690	2,407	0,525	**0,000**	1,060	-0,109
Golem	2,381	-0,261	-0,034	5,681	1,769	-0,203	-1,060	**0,000**	-0,196
Singular	2,534	-0,107	-0,008	2,393	2,157	0,127	0,109	0,196	**0,000**

The results reveal that the two largest cryptocurrencies measured by market capitalization, Litecoin (Currency) and Ethereum (Protocol), are net transmitters of volatility to all other cryptocurrencies, with the exception that Litecoin is a net receiver from Ethereum. Excluding Waves (Protocol), all medium- and low market capitalization cryptocurrencies are net receivers. On average, our findings suggest that Ethereum is the most significant provider of volatility between these nine cryptocurrencies, while Litecoin is the cryptocurrency affected the most by the volatility from the nine cryptocurrencies.

The results presented above are generated using the full-sample analysis and captures only the average behavior of the volatility spillover during the sample period. As a robustness check, we conduct a rolling window analysis. By using a rolling-window analysis, it is possible to also capture the time-varying volatility spillover during this time-period.

6.2.2 Rolling-Window Analysis of Volatility Spillover

We use a 100-day window in our rolling-window tests and plot the results in Figure 1, for the total volatility spillover index generated using equation 4.10. At first glance, the total volatility seems to have considerable fluctuations over the time-period, with a maximum and a minimum of approximately 90% and 14% respectively. The average total volatility spillover is 41,5 % with a standard deviation of 14,8% during the time-period. Comparing the time-varying average volatility with the average volatility generated from the full-sample analysis, the full-sample average total volatility is lower, but still within one standard deviation. Figure 1 shows no sign of any clear trend in the volatility spillover index, which gives evidence that the volatility spillover is time-varying in the sample period.

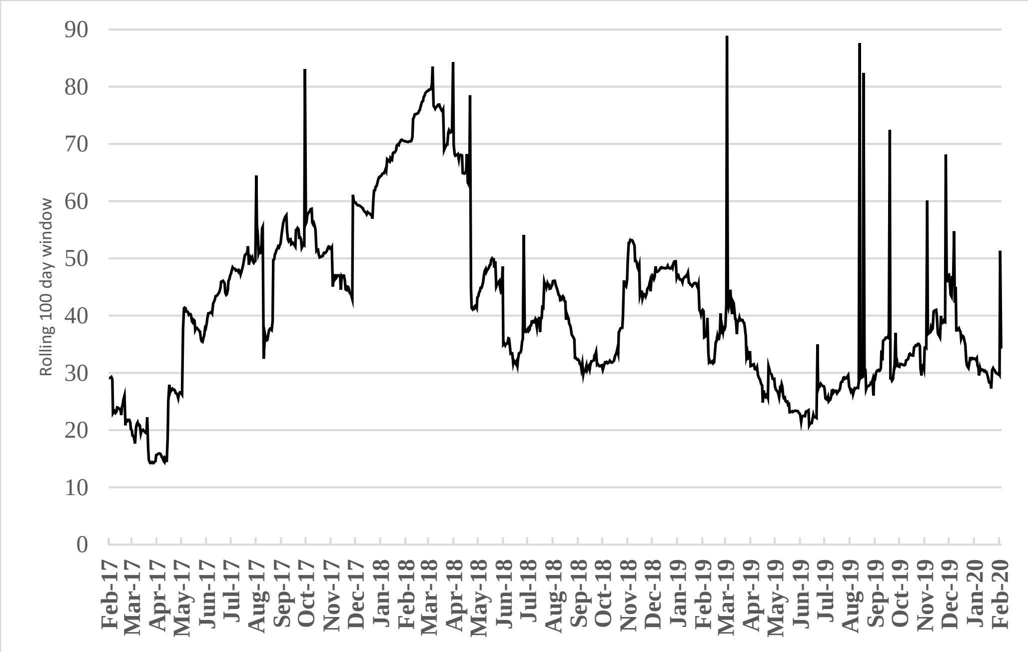

Figure 1: Total volatility spillover for all cryptocurrencies without COVID-19.

From Figure 1 there are clearly several spikes in the total volatility spillover and some periods with overall higher volatility spillover. Antonakakis et al. (2019) shows that the level of market uncertainty corresponds to a strong or weak connectedness within the cryptocurrency market. Therefore, the high volatility spillover over time reflects the interdependence in terms of volatility within the cryptocurrency market. To address the rapid increase in connectedness within the cryptocurrency market, these are some possible causations for these shocks.

From Figure 1 we see an increase in connectedness during 2017 and early 2018. This can be linked to two major trading countries of cryptocurrencies, China and South Korea (Mandz, 2020) having uncertainty about the future of cryptocurrencies. There were news of China's regulation on the ban of ICOs, a fundraising process that is cryptocurrency based (Deng, 2017), while there was a rumor in early January 2018 speculating that South Korea would impose a ban on trading cryptocurrency (Kharpal, 2018). The overall increased uncertainty in the cryptocurrency market between 2017 and 2018 may be associated with the large increase in volatility spillover within the cryptocurrency market. This may have set the precedent for average higher volatility spillover as a norm and might be an explanatory factor for the relatively higher overall spillover post this period.

6.2.3 Analysis of Categories

As explained in Chapter 3, the cryptocurrency market can be divided into three categories, namely Currency, Protocol and dApps. Corbet et al. (2020b) argues that the different categories react differently to FOMC announcements and should therefore not be viewed as one category. Building on the work conducted by Corbet et al. (2020b), where the assumption is that there are three categories, the focus of this part of the analysis is towards the categorization of the cryptocurrencies based on their primary use. The *Currency* category includes Litecoin, Monacoin and Counterparty, the *Protocol* category contains Ethereum, Waves and LBRY Credits, and the *dApps* category is represented by Digixdao, Golem and Singular DTV.

6.2.3.1 Full-sample analysis between categories

For comparison, we reproduce Table 14.

Table 14: Volatility spillover table for all cryptocurrencies without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	Litecoin	Monacoin	Counterparty	Ethereum	Waves	BRYCredits	Digixdao	Golem	Singular DTV	Directional FROM others
Litecoin	**49,082**	2,732	0,519	19,762	13,867	4,680	3,051	3,966	2,341	50,918
Monacoin	6,325	**77,749**	1,367	3,682	4,172	3,252	1,343	1,144	0,967	22,251
Counterparty	1,312	0,631	**95,144**	1,111	0,915	0,542	0,129	0,139	0,077	4,856
Ethereum	18,470	2,156	0,522	**49,667**	11,998	4,886	3,931	5,775	2,596	50,333
Waves	14,397	1,941	0,748	12,655	**56,828**	5,125	1,642	4,423	2,241	43,172
LBRYCredits	9,247	3,277	0,694	8,217	8,340	**63,659**	1,666	3,556	1,345	36,341
Digixdao	5,397	2,617	0,345	7,621	4,049	2,191	**74,816**	2,261	0,703	25,184
Golem	6,347	0,883	0,106	11,456	6,192	3,353	1,201	**69,229**	1,234	30,771
Singular DTV	4,875	0,860	0,068	4,989	4,398	1,472	0,812	1,430	**81,096**	18,904
										Total spillover index:
Directional TO others	66,370	15,098	4,367	69,493	53,930	25,501	13,774	22,693	11,505	31,414 %
Directional including own	115,842	92,955	99,693	113,214	108,642	89,316	89,164	99,260	91,915	
Net spillover	15,452	-7,153	-0,488	19,160	10,757	-10,840	-11,410	-8,078	-7,399	

Table 14 indicates that all Protocols seem to have a lower average own-variance share compared to the average own-variance share of the other categories. This can be evidence that Protocols have a stronger connectedness to the market than the other categories. On average the table suggests that Protocols are net transmitters to both categories (except for Litecoin from the Currency category). Based on these findings, the results show that the Protocol category is the largest contributor to uncertainty in the market. From Table 14, the results imply that the dApps category on average tends to be the largest net receivers, subsequently making them the smallest contributor to uncertainty in the market. Further, derived from Table 14, the Currency category is a large net transmitter of volatility in Litecoin. However, the other Currencies are net receivers with Counterparty receiving almost as much as it transmits volatility.

6.2.3.2 The Relationship between dApps and Protocols

Corbet et al. (2020b) explains in their study the relationship between Ethereum and decentralized applications (also referred to as tokens), and illustrates how Ethereum token holders could benefit from the growth of the decentralized applications built upon the Ethereum protocol. To better understand the relationship between the Protocol and the decentralized applications built upon them, we present a quick explanation of the terms and a simple example.

As noted in Chapter 3, decentralized applications are front-end applications built upon a different back-end application in the form of a smart contract. The code for the decentralized application is created and uploaded into the platform of the protocol. The machine code will have several operations that needs to be executed by the protocol layer. Using Ethereum as an example, each operation requested by the decentralized application has a cost, and the decentralized application built upon Ethereum (also referred to as ERC-20 tokens) need to pay this cost to execute the operations. The cost is represented by a currency Ethereum have created named *gas* (Wood, 2020). The *gas* price is constant and pre-defined for each operation required from the decentralized application. The *gas* cost is then translated into Ether, the cryptocurrency of Ethereum. The reason that the cost does not translate directly into Ether is to separate the price of an operation with the price of Ether on the market. So, instead of altering the *gas* price for each operation, the value of the *gas* price in Ether is changed to represent the value of the work. As the decentralized application grow in terms of size, the requests for more operations increases which again increases the demand of Ether. Therefore Corbet et al. (2020b) suggest that holders of Ethereum tokens not only benefit from growth in Ethereum, but also from the growth of any application built upon the platform.

Table 14 shows that there is considerable connectedness between Ethereum and the dApps, however, it should be noted that due to data limitations all selected dApps are based on Ethereum thus this result is not surprising. However, Table 14 also suggests that the amount of volatility transmitted to the dApps from Ethereum is on average higher than the volatility received from dApps. This shows that Ethereum affects the dApps more than the dApps affect Ethereum in terms of volatility. In light of what Corbet et al. (2020b) discuss in their paper, the movements of the value of the dApps seems to be transferred to Ethereum, which can be one of the reason for the connectedness between the two categories. On the other hand, this effect seems to be surpassed by the effect Ethereum has on the dApps in terms of volatility. Therefore, Ethereum is an average net transmitter of volatility to the selected dApps.

6.2.3.3 Full-Sample Analysis of Volatility Spillover

As a robustness check for the findings found in chapter 6.2, a full-sample analysis of volatility spillover has been conducted between equally weighted indexes based on the different categories explained in Chapter 3. Because of the considerable difference in market capitalization between the cryptocurrencies, a value weighted index would most likely only capture the volatility spillover associated with the high market capitalization cryptocurrencies. An equally weighted index represents each cryptocurrency equally and is therefore a better fit to this analysis. Table 16 represents the full-sample volatility spillover index.

Table 16: Volatility spillover table for the cryptocurrency category indexes (EWI Currency, EWI Protocol, EWI dApps) without COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	EWI Currency	**EWI Protocol**	**EWI dApps**	**Directional FROM others**
EWI Currency	**89,372**	7,692	2,936	10,628
EWI Protocol	7,220	**79,850**	12,930	20,150
EWI dApps	3,006	15,160	**81,834**	18,166
				Total spillover index:
Directional TO others	10,226	22,852	15,865	17,522 %
Directional including own	99,598	102,702	97,700	
Net spillover	-0,402	2,702	-2,300	

From Table 16, the total volatility spillover between the categories is 17,522%. This reduction in total volatility spillover compared to Table 14 may be caused by the creation of the equally weighted indexes, which reduces some idiosyncratic volatility from each individual cryptocurrency. Another possible reason is that compared to Table 14, Table 16 does not include volatility spillover between the cryptocurrencies within the categories hence, a lower total volatility spillover. Our results show that there is a stronger connectedness between Protocol - dApps than Currency - Protocol and Currency - dApps, which can be driven by the relationship between Ethereum and the selected dApps. Table 16 shows that the Protocol category is the category with the strongest connectedness. This is consistent with the findings in Table 14, where the average of the three Protocols in the sampled data have the lowest own-variance share compared to the two other categories. Still, the own-variance shares explain most of the volatility in each category. Further, both the Currency- and dApps category are net receivers and the Protocol category is a net transmitter on average, confirming the findings in Table 14.

Highlighting the direction of the spillover, Table 17 introduces the net pairwise spillover between the categories.

Table 17: Net pairwise spillover table for the cryptocurrency category indexes (EWI Currency, EWI Protocol, EWI dApps) without COVID-19.

Net pairwise spillover

	EWI Currency	EWI Protocol	EWI dApps
EWI Currency	0,000	0,472	-0,070
EWI Protocol	-0,472	0,000	-2,230
EWI dApps	0,070	2,230	0,000

Derived from the net pairwise spillover from the full-sample analysis, Protocol is a net transmitter on average to both Currency and dApps. Additionally, Currency is a slight marginal transmitter to dApps on average, but overall a net receiver of volatility. From Table 14, only one Currency is a net transmitter (Litecoin), while the other two (Monacoin and Counterparty) are net receivers. The EWI for Currency gives all three sampled cryptocurrencies equal weight, consequently the two net receivers cause the overall EWI Currency to be a marginal net receiver.

6.2.3.4 Rolling-Window Analysis of Volatility Spillover

Finally, a rolling window analysis of volatility spillover with a 100-day window is performed. Constant with the previous rolling window analysis, the results for the volatility spillover between categories is generated using equation 4.10.

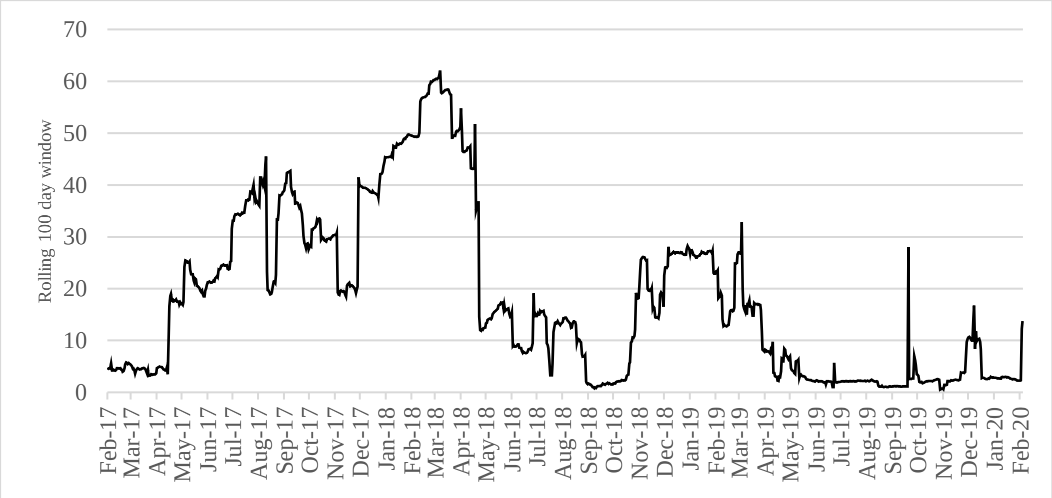

Figure 2: Total volatility spillover for all cryptocurrency category indexes without COVID-19.

Volatility spillover between categories have relatively large fluctuations during the time-period. However, in contrast to the total volatility spillover in Table 14, the overall volatility spillover is lower on average. This may be an effect of lower idiosyncratic movements because of indexing. Therefore, large shocks have a seemingly lower effect for the indexes compared to the overall spillover, resulting in less substantial spikes in Figure 2. The maximum and minimum volatility spillover is approximately 62% and 1% respectively, with an estimated average volatility spillover between categories of 18% with a standard deviation of 16%. The findings are consistent, seemingly creating indices lowers the volatility spillover compared to the overall spillover. Comparing the time-varying average volatility with the average volatility generated from the full-sample analysis, the full-sample average total volatility is roughly equal and within one standard deviation, indicating similar results. Furthermore, Figure 2 shows no sign of any clear trend in the volatility spillover index, which gives evidence that the volatility spillover is time-varying in the sample period.

When investigating the connectedness between the nine selected cryptocurrencies, we find a relatively strong connectedness. This is consistent with our findings from subchapter 6.1, where the results show that most of the volatility in our proxy for the cryptocurrency market comes from within the market. By further studying Table 14, our results indicate that there is a relationship between market capitalization and the connectedness with the rest of the selected cryptocurrencies. The higher market capitalization cryptocurrencies have a stronger connectedness with the rest of the cryptocurrencies, while the lower market capitalization cryptocurrencies have weaker connectedness with the rest of the cryptocurrencies.

When shifting the focus over to the categorization of the cryptocurrencies, it appears from the result that the Protocol category has the strongest connectedness on average. There is also considerable connectedness between Ethereum, and the decentralized applications built upon Ethereum’s protocol, which is, to our knowledge, the first time this relationship has been tested. By indexing the categories, the relationship between the categories in terms of volatility spillover is made clearer. The Protocol category is a net transmitter of volatility, while Currency and the dApp category are net receivers. The results also indicate that the connectedness between the protocol category and the dApp category is stronger than the respective connectedness with the Currency category. The results from indexing also suggest that most of the volatility comes from within each category, as shown from their own-variance shares.

As the first to look at the connectedness within the cryptocurrency market with the focus on the categorizations, a lot of useful information have been revealed. As a cryptocurrency investor, knowing the characterizations of the different categories could help construct a more diversified portfolio when investing in the cryptocurrency market.

6.3 COVID-19

In the beginning of this thesis, COVID-19 was assumed to be a small virus contained within China. However, throughout the process of writing this thesis, COVID-19 evolved into a pandemic. The ramifications of COVID-19 were clearly seen within financial markets. Consequently, it is interesting to see the initial effect that the pandemic has had on the connectedness within the cryptocurrency market and the connectedness with other financial markets during this period. Szado (2009) find that volatility levels measured by VTX experienced significant increases during the financial crisis and Diebold and Yilmaz (2012) find that due to the significant increase in volatility, the connectedness between financial markets increased during and after the financial crisis in 2007. The two financial markets included are the S&P 500 and Gold, since they are used for previous analysis within this thesis. However, because the pandemic is still ongoing, we will only be able to capture the timeframe up until June 2020. Further research should investigate the long-term effects of volatility spillover within the cryptocurrency market and between the cryptocurrency market and other financial markets.

Like the previous analysis in 6.1 and 6.2, this part of the analysis presents the same structure of empirical results but also includes data from the ongoing pandemic. This part will be divided into two sections where the first one focuses on the effect COVID-19 had on the cryptocurrency market. The second part will investigate the volatility spillover effects between the cryptocurrency market, S&P 500, and Gold. Gold and the S&P 500 are used in this analysis to see how the cryptocurrency market behaves, in terms of volatility, against large financial markets.

6.3.1 Full-Sample Analysis of Volatility Spillover between nine cryptocurrencies

Table 18 presents the total, directional and net spillovers from the full-sample analysis of the volatility spillover between the nine cryptocurrencies, including the COVID-19 dates. It can be observed from Table 18 that spillover effects accounts for approximately 33.5% of the volatility in each cryptocurrency. Compared to the previous dates that excluded the COVID-19 dates, the total average spillover has increased by approximately 2 percentage points. Overall, the results seem to stay mostly the same, where their own variance share still is the main provider of volatility in each cryptocurrency. Apart from Counterparty, the connectedness for all other cryptocurrencies has increased marginally, relative to their own-variance share.

Table 18: Volatility spillover table for all cryptocurrencies with COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	Litecoin	Monacoin	Counterparty	Ethereum	Waves	BRYCredits	Digixdao	Golem	Singular DTV	Directional FROM others
Litecoin	**46,277**	2,857	0,438	20,340	14,843	5,027	3,333	4,442	2,441	53,723
Monacoin	6,574	**76,645**	1,379	3,970	4,495	3,160	1,525	1,344	0,908	23,355
Counterparty	1,175	0,669	**95,553**	0,997	0,809	0,448	0,140	0,145	0,064	4,447
Ethereum	19,498	2,266	0,430	**46,405**	13,181	5,178	4,210	6,113	2,719	53,595
Waves	15,751	2,104	0,659	13,777	**53,191**	5,317	1,966	4,939	2,296	46,809
LBRYCredits	9,790	3,158	0,570	8,716	8,583	**62,336**	1,797	3,713	1,336	37,664
Digixdao	6,186	2,818	0,341	8,227	4,648	2,338	**72,128**	2,547	0,766	27,872
Golem	7,346	1,037	0,102	12,113	7,160	3,551	1,447	**65,969**	1,274	34,031
Singular DTV	5,327	0,857	0,052	5,404	4,577	1,549	0,890	1,466	**79,877**	20,123
										Total spillover index:
Directional TO others	71,648	15,767	3,971	73,544	58,297	26,569	15,309	24,710	11,803	33,513 %
Directional including own	115,842	92,955	99,693	113,214	108,642	89,316	89,164	99,260	91,915	
Net spillover	17,925	-7,589	-0,476	19,949	11,488	-11,095	-12,563	-9,321	-8,319	

Regarding the net volatility spillover, the inclusion of COVID-19 dates has not affected the overall directional spillover for the respective cryptocurrencies. Apart from Counterparty, the net spillover for each cryptocurrency has marginally increased, only making them a larger net transmitter or net receiver. Looking at the different categories, all Currencies (except for Litecoin) and dApps are net receivers. However, Protocols seem to have slightly stronger connectedness for all selected cryptocurrencies when COVID-19 dates are included.

6.3.2 Rolling-Window Analysis of Volatility Spillover between nine cryptocurrencies

To see the time-varying effects of COVID-19 on the cryptocurrency market, a rolling window analysis has been conducted. The results from the total volatility spillover index between the nine cryptocurrencies is presented in Figure 3. Inclusion of the COVID-19 dates has led to a marginally higher average total spillover of 43,2 % with a higher standard deviation of 15,8%. From Figure 3, it is apparent that the market experienced a spike in connectedness in March 2020. As the COVID-19 was declared a pandemic as of 11.03.2020 by WHO, this spike is most likely due to that (WHO, 2020).

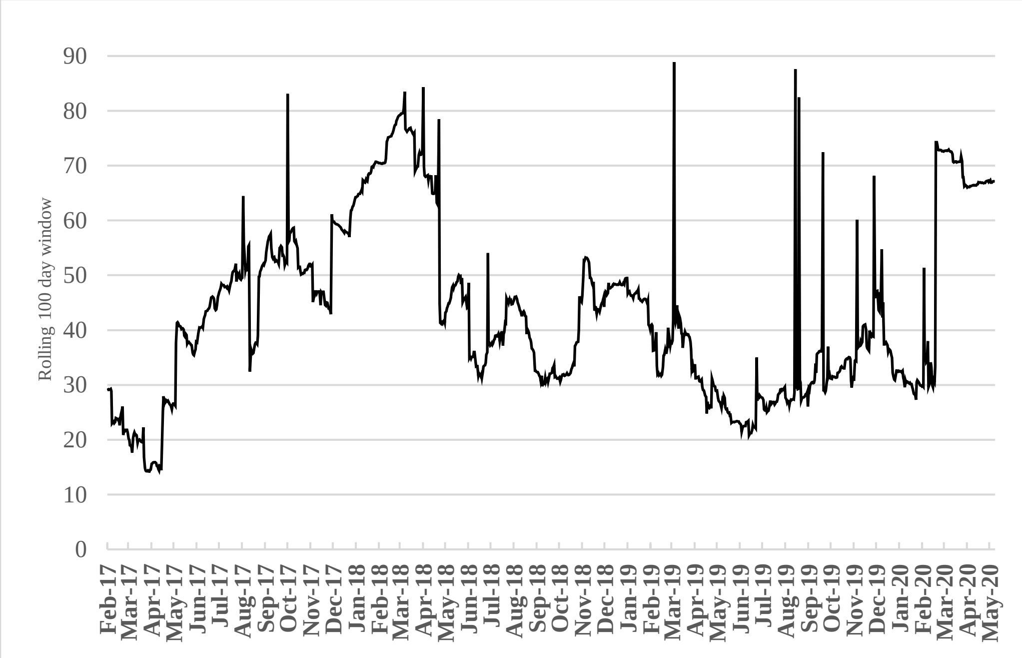

Figure 3: Total volatility spillover for all cryptocurrencies with COVID-19.

By studying Figure 3, the results indicate that the total spillover index seems to stabilize around a relatively high total spillover during the pandemic after the marginal drop from the highest peak in March 2020. An interesting note for further studies will be to examine if the total volatility spillover index will stabilize around a relatively high total volatility spillover, as seen from the first months of the pandemic, or if it will stabilize closer to the normal level of total volatility spillover.

It is interesting to note that as seen from the full-sample analysis and the rolling-window analysis, the total spillover index has increased. However, the total spillover has not surpassed several spikes experienced during the 3,5-year data sample, indicating an overall volatile market with strong connectedness. This is consistent with the findings in Omane-Adjepong and Alagidede (2019) who find that it is probable for there to exist a strong interconnectedness within the cryptocurrency market. From Figure 3, the connectedness within the cryptocurrency market has increased but since it is overall an interconnected market, the average total spillover has not substantially increased. Further studies could examine how the magnitude of the total spillover index is affected by the whole period of the pandemic.

6.3.3 Full-sample analysis between VWI, EWI, S&P 500, and Gold

Campbell et al. (2002) and Mensi et al. (2013) note that there is an increase of volatility and volatility connectedness between markets during a financial crisis. As the pandemic led to a world-wide health crisis and an economic market crisis, it is useful to examine the initial effects that the pandemic had on connectedness between the markets. First, in this part of the analysis we will investigate the effect of volatility connectedness between the VWI, S&P 500, and Gold to see if the connectedness between these markets increased after the declaration of the COVID-19 pandemic. Then as a robustness check, we analyze the volatility connectedness between EWI, S&P 500 and Gold.

Table 19 represents the full-sample analysis of the total, directional, and net volatility spillover between VWI, S&P 500 and Gold when including the COVID-19 dates available. VWI captures the weights based on market capitalization and therefore, the EWI will act as a robustness check as the index gives equal weights regardless of market capitalization.

Table 19: Volatility spillover table for the indexes (VWI, S&P500 and Gold) with COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	S&P 500	**Gold**	**VWI**	**Directional FROM others**
S&P 500	**80,354**	18,764	0,882	19,646
Gold	43,404	**55,022**	1,573	44,978
VWI	3,107	4,130	**92,764**	7,236
				Total spillover index:
Directional TO others	46,511	22,894	2,455	23,953 %
Directional including own	126,865	77,916	95,219	
Net spillover	26,865	-22,084	-4,781	

Consistent with the findings earlier in this chapter (Table 11), Table 19 indicates that most of the volatility spillover for the cryptocurrencies comes from within the cryptocurrency market, even during a crisis period. However, comparing the results to Table 11, there are multiple changes. The total spillover index increased from approximately 1% to approximately 24%, implying that the crisis has strengthened the overall connectedness. However, the largest changes are between S&P 500 and Gold. For VWI the own-variance share accounts for 92,764%. This suggests that the cryptocurrency market has a stronger connectedness with other financial markets during a crisis, but that most of the volatility spillover still comes from within the cryptocurrency market.

Table 20: Net pairwise spillover table for the indexes (VWI, S&P 500 and Gold) with COVID-19.

Net pairwise spillover			
	S&P 500	**Gold**	**VWI**
S&P 500	0,000	-24,640	-2,225
Gold	24,640	0,000	-2,556
VWI	2,225	2,556	0,000

Table 20 represents the net pairwise spillover from the full-sample analysis. The results indicate that S&P 500 is a large net transmitter to Gold and a net transmitter to VWI. Gold is also a net transmitter to VWI and consequently VWI is an overall net receiver of volatility spillover.

Table 21: Volatility spillover table for the indexes (EWI, S&P500 and Gold) with COVID-19 dates. Own variance shares are displayed in the diagonal aspects. The off-diagonal aspects display the cross-variance shares.

	S&P 500	**Gold**	**EWI**	**Directional FROM others**
S&P 500	**80,052**	18,992	0,956	19,948
Gold	43,121	**55,970**	0,909	44,030
EWI	1,571	2,704	**95,725**	4,275
				Total spillover index:
Directional TO others	44,692	21,696	1,865	22,751 %
Directional including own	124,744	77,665	97,590	
Net spillover	24,744	-22,335	-2,410	

Because of the structural difference between EWI and VWI, EWI should expect less connectedness with other financial markets during a crisis. The reason is that small market capitalization cryptocurrencies have a larger weight in EWI than VWI. When including the pandemic into the dataset, analyzing the EWI, Table 21 suggests that this hypothesis is correct. Furthermore, the cryptocurrency market has received more volatility from both the S&P 500 and Gold compared to without COVID-19 dates.

Table 22: Net pairwise spillover table for the indexes (EWI, S&P 500 and Gold) with COVID-19.

Net pairwise spillover			
	S&P 500	**Gold**	**EWI**
S&P 500	0,000	-24,129	-0,615
Gold	24,129	0,000	-1,795
EWI	0,615	1,795	0,000

Derived from net pairwise spillover from the full-sample analysis, the EWI is an overall net receiver of volatility spillover from S&P 500 and Gold. However, comparing it to the net pairwise spillover with VWI, EWI is a smaller net receiver.

This part of the analysis shows that the overall connectedness both within and between the financial markets increases when including the COVID-19 dates. However, the average total volatility within the cryptocurrency market only increases by two percentage points, indicating a low increase in the average connectedness. However, as seen in the rolling-window analysis, it is apparent that the total volatility spillover within the cryptocurrency market experienced a spike after the declaration of the COVID-19 pandemic.

By studying the connectedness between our proxy for the cryptocurrency market, S&P 500, and Gold, it appears from the result that most of the increase in connectedness is between S&P 500 and Gold. Consequently, the bottom line is that the inclusion of the COVID-19 dates does not change the overall results substantially for the cryptocurrency market.

7 Conclusion

In this thesis, we have analyzed two time periods. The first contains data from November 2016 to February 2020, while the second period extends until June 2020. The datasets contain nine cryptocurrencies, S&P 500, Gold, and Copper. Using the datasets, we have investigated the volatility spillover between the markets both before and during the initial phase of the COVID-19 pandemic. Further, we have studied the volatility spillover within the cryptocurrency market and finally, between the different categories within the cryptocurrency market both before and during COVID-19. The cryptocurrencies for each category are chosen based on their market capitalization and their primary use. We have utilized the generalized spillover index developed by Diebold and Yilmaz (2009, 2012) in order to analyze the spillovers.

The first analysis is conducted without the COVID-19 dates and is between EWI, VWI, S&P 500, and Gold. The results show an overall weak connectedness between the markets. The connectedness is marginally stronger between S&P 500 and Gold, while the connectedness between these two markets and both EWI and VWI is marginally weaker. The results show that most of the volatility comes from within each market. To test if the low spillover effects between EWI and VWI against the other two financial markets stems from the low market capitalization, the commodity Copper is tested because of the similar size in market capitalization. The results imply a stronger connectedness between Copper, S&P 500, and Gold, implying that the weak connectedness across markets is most likely due to the independence of the cryptocurrency market.

From the analysis of the cryptocurrency market, there seems to be a relation between market capitalization and the within market connectedness of the nine cryptocurrencies. Furthermore, the results imply that the same relation is consistent within each category, indicating that the highest market capitalization cryptocurrency has the strongest connectedness. The cryptocurrencies with the lowest market capitalization within each category seem to have the weakest connectedness, further confirming the relation between market capitalization and connectedness. Our results imply that the connectedness within the market is volatile throughout the period, ranging from 14% to 90%. The increase in connectedness during 2017 and early 2018 may have been related to the uncertainty of the future of cryptocurrencies in China and South Korea, two of the major trading countries of cryptocurrencies. The overall increased uncertainty between 2017 and 2018 may have set the precedent for average higher volatility spillover and might be an explanatory factor of the increased volatility spillover post this period.

Shifting the focus to the categories, the results show that the Currency category has one large net transmitter of volatility (Litecoin), one large net receiver (Monacoin), and one marginal net receiver (Counterparty). The Protocols are net transmitters on average, having two large net transmitters (Ethereum and Waves) and one large net receiver (LBRY Credits). Finally, dApps is a net receiver on average, with all being large net receivers.

The results from the analysis between equally weighted indexes of the categories, are consistent with our previous findings. The Currency category and Protocol seem to transmit and receive approximately the same amount of volatility, with Protocol being a marginal net transmitter. Further, Currency marginally transmits volatility to dApps but is overall a net receiver. Out of the three categories, the Protocol category has the strongest connectedness within the cryptocurrency market. We also found that between Protocols and dApps, Protocol is a net transmitter, suggesting a potential stronger relationship between the categories. As explained in Corbet et al. (2020b) there is a natural relationship between Protocol currencies and the decentralized application built upon the protocol because of the cost of operations done by the protocol layer. The results indicate that there is in fact a connectedness between Ethereum and the decentralized applications built upon the Ethereum protocol.

The results when including dates during the COVID-19 pandemic indicate a stronger connectedness within the cryptocurrency market. Even though there was a spike most likely due to the pandemic, the total average volatility spillover within the market increased by two percentage points. This may be because of an already strong connectedness within the cryptocurrency market before the COVID-19 pandemic. Comparing the indexes consisting of the nine cryptocurrencies with S&P 500 and Gold, we find an overall stronger connectedness when including dates during the pandemic. However, the stronger connectedness seems to be driven by the connectedness between S&P 500 and Gold. Even though the cryptocurrency market becomes more connected with the other two financial markets, the results indicates that it is still mostly independent when including the COVID-19 dates.

The thesis contributes to the discussion of volatility spillover and connectedness in the cryptocurrency market. Unlike most previous research in this area our study dives deeper into the categories of the cryptocurrency market and explores the relationship between these categories in terms of spillover effects. Our thesis finds common relations in terms of volatility for the different categories, which strengthens the importance of the categorization of the cryptocurrency market. This study also captures the initial effect the COVID-19 pandemic had on the cryptocurrency market as well as the connectedness between the cryptocurrency market and other financial markets.

Finally, a limitation to our thesis is that the category dApps does not have many currencies with sufficient available data. Therefore, as the cryptocurrency market matures with time, future research can include more cryptocurrencies with adequate data to make justifiable observations. Consequently, it will also be interesting to dive deeper into the relationship between more Protocols and dApps built on the different Protocols. Furthermore, as our dataset is limited to dates during the initial parts of COVID-19, it would be interesting to see the full effect both short-term and long-term of COVID-19 in the cryptocurrency market in terms of connectedness and volatility spillover.

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