Louvain School of Statistics, Biostatistics and Actuarial Sciences
Université catholique de Louvain
Louvain-la-Neuve
Belgium

Analysis of cryptocurrency connectedness based on network to transaction volume ratios

A thesis submitted in partial fulfillment of the requirements for the master degree in Data Science

by

Sabrine Majeri

Thesis Committee:
Prof. Christian Hafner (*Promotor*)
Prof. Donatien Hainaut

Louvain-La-Neuve
May 2021

Acknowledgment.

I would like to express my sincere gratitude to my supervisor Prof. Christian Hafner for his guidance, valuable advice, continuous support during these months and also for providing me with the golden opportunity to do this wonderful project on cryptocurrencies.

I would like to also thank my family and friends for their love and unconditional support. And I will forever be grateful to my father for everything he has done for me, and for believing in my ability to be successful.

Table of contents

List of Figures

List of Tables

Abstract

Using a spillover index approach and its variants, we examine the connectedness between 39 cryptocurrencies (among the world's top 400 by market cap as of February 2021). As the main feature, we use the so-called Network to Transaction (NVT) ratio, which is the market capitalization divided by an estimate of the on-chain transaction volume, which makes different cryptos comparable and serves as an indicator for their usefulness. We build a connectedness network connecting these 39 cryptocurrencies based on the framework of variance decompositions in a vector autoregression model. We also use LASSO to reduce the number of parameters in the VAR model due to the large dimensionality of the data. We find that NVT connectedness or spillover effect is not necessarily related to market capitalization, as we have large and small cryptocurrencies by market cap that propagate large NVT shocks (eg Litecoin, Dogecoin, Bitcoin Cash(bch), OMG Network and Decentraland(mana)). More importantly, the largest issuer of NVT shocks for other cryptocurrencies is OMG Network (small cryptocurrency by market cap), which receives less public attention. We also find that bitcoin is not the dominant cryptocurrency when it comes to NVT shocks, as it has a small contribution to the spillover on other altcoins. Therefore, the NVT values of altcoins are not determined by bitcoin. Additionally, our work provides new insights about cryptocurrencies; those relying on Proof of Stake and Delegated Proof of Stake as a consensus mechanism are the smallest receivers of NVT spillovers from other cryptocurrencies. These assets are also the least interconnected with each other. Therefore, market participants may be interested in investing in this group of altcoins to obtain diversified risk. Mining cryptocurrencies that are relying on PoS is more efficient because they do not require high electricity costs or high material purchase costs to verify transactions. We also find that the cryptocurrencies used for privacy are the least interconnected and receive small spillovers from other assets, which may also attract the attention of market participants.

Keywords: Vector Autoregressions, ICA, LASSO, Networks, Cryptocurrencies

1 Introduction

After the 2008 financial crisis that led to growing suspicions towards traditional financial systems, Bitcoin has been introduced by Satoshi Nakamoto in 2009 which is the first decentralized peer-to-peer payment network that is powered by its users with no central authority or middlemen.

This peer-to-peer electronic currency was created via innovative technology, called Blockchain, which registers all the transactions and stores them into transparent blocks. These transactions are only validated after authentication and verification by the designated network participants called miners, who ensure that only genuine transactions are propagated across the network.

Over the years, Bitcoin has retained its position as the cryptocurrency with the greatest market capitalization. By the first of February 2021, Bitcoin's market capitalization has surpassed 894 billion US dollars (USD) according to coinmarketcap website.

Following Bitcoin's creation, many alternative cryptocurrencies collectively referred to as altcoins, emerged using the same blockchain technology.

The first Bitcoin alternative was Ethereum (ETH), which is a decentralized software platform that enables Smart Contracts and Decentralized Applications to be built and run without fraud, control, or interference from a third party. Ether's market capitalization was roughly 19% of Bitcoin's size in January 2021.

Litecoin(LTC) is also one of the most popular altcoins, which is based on an open-source global payment network. It has a faster block generation rate and hence offers a faster transaction confirmation time than bitcoin. As of January 2021, Litecoin had a market capitalization of $10.1 billion, making it the sixth-largest cryptocurrency in the world.

Moreover, there are a lot of important altcoins other than Ethereum and Litecoin, naming a few: Cardano (ADA), Polkadot (DOT), Bitcoin Cash (BCH), Stellar (XLM), Tether (USDT), Dash... These altcoins have gained growing market shares with whatever they are used for (identity verification, security, data storage, payments, etc). Therefore, they have attracted investors' attention.
Essentially, altcoins creators are trying to correct what they consider to be a flaw in Bitcoin's design. Although some of these currencies can have impressive features that Bitcoin has not, none of them could match the level of security achieved by the Bitcoin network.

Cryptocurrencies, unlike traditional assets, are completely decentralized and are not linked or regulated by any government, which can ensure anonymity, low cost and fast speed of peer-to-peer transactions based on crypto protocols. As a consequence, in the last few years, Cryptocurrencies have witnessed unprecedented growth in price and market capitalisation, where the total market capitalization has surpassed $2 Trillion in 2021, and there are over 4,000 different cryptocurrencies in existence as of January 2021. However, it is believed that the top 20 cryptocurrencies make up nearly 90 per cent of the total market.

The number of existing cryptocurrencies is so high because they are relatively costless to create and because a large portion of these assets has little to no trading volume, so they might not be significant. As a result, many investors were concerned with the valuation of these revolutionary digital assets, wanting to detect whether they are overvalued or undervalued based on daily transactions. To put it in other words, these market participants question whether cryptocurrencies are a valuable opportunity investment and their current prices reflect their fundamental value, or whether they are just fictitious currencies forming speculative bubbles.

In 2017, coinmetrics website introduced the network value-to-transaction (NVT) ratio as a method of valuing crypto-asset network. It is defined as the ratio of market capitalization and the on-chain transaction volume, and hence gives an estimator of the usefulness of a given crypto. It is comparable across cryptos and can be viewed as the analogue of a P/E (Price to Earnings) ratio for stocks. It tracks the daily USD volume transmitted through the blockchain and measures this against the market value (as measured by market capitalisation) – just like the P/E Ratio measures the stock price against earnings.

The NVT metric quantifies essentially the value of the network against its usefulness as a payment network. Therefore, it helps investors spot cryptocurrencies bubbles and investment opportunities. High NVT ratios hint at possible overvaluations, low ratios at undervaluations.

In this study, we will be using an adjusted measure of the NVT metric, proposed by coinmetrics, because from the perspective of an analyst or economist it is useful to isolate only the meaningful economic transactions to render a more robust analysis of the economic volume. This adjusted measure attempts to correct the raw NVT measure for change transactions that are not genuine payment transactions.
Change transactions are common in cryptocurrencies. If a person A has to pay a person B 8 bitcoin, for example, but A has 10 bitcoins in his/her wallet, then a payment of 10 bitcoins is done from A to B, and a payment of 2 bitcoins from B to A. Without adjustments, the total transaction volume would be 12 rather than 8 bitcoins. coinmetrics proposes an algorithm that corrects for this type of change transactions.
In consideration of that, the NVT ratio uses adjusted transaction volume for the purpose of creating a purer measure of the actual usage of the chain, as it removes transaction volumes due to change transactions.

Based on the NVT ratio, we construct a network, aiming to explore, identify and evaluate network connectedness or spillovers among different cryptocurrencies at a system-wide level, which is the main purpose of this capstone.
Moreover, we want to determine if Bitcoin is the dominant cryptocurrency since we know that it has the highest market capitalization, or whether there is another cryptocurrency that has a stronger impact on other cryptos through higher connectedness and spillover.

Investigating network connectedness contributes to understanding the information transmission mechanism in the cryptocurrency market and provides useful information for market participants such as investors as this would help them choose a suitable cryptocurrency to adjust their asset portfolio based on their risk preferences.

Furthermore, this could be helpful for miners, as the mining process requires significant energy consumption and large material purchase costs, leading miners to invest less in cryptos that have negative price trends.
Hence, network connectedness and spillovers across assets would be beneficial to mine the less interconnected cryptocurrencies, so as to obtain diversified risks that arise from price fluctuations in the crypto market.

In order to investigate the diversification and hedging traits of the aforementioned cryptocurrencies, we consider using vector autoregressive models, see e.g. Sims (2002), which helps to capture the co-movements between these assets.

In addition, since we are analyzing high-dimensional data (our sample includes 39 cryptocurrencies), we exploit the least absolute shrinkage and selection operator (LASSO) method , which is a regression analysis method used to increase the prediction accuracy and interpretability of the statistical model through variable selection and regularization, and it is used in our context to reduce dimensionality and shrink the sample when estimating VAR parameters.

We will also see how to choose the order of the model and validate the chosen one. Then, we will define one of the most useful concepts related to the dynamic relations that could exist between the variables of the system which is the the forecast error variance decomposition.
We further examine this concept in order to transfer the proportions of these variances into directional network connectedness.

Using the spillover index approach and its variants (Diebold Yilmaz, 2009, 2012, 2014), we measure both total and directional network connectedness across the cryptocurrencies.
The results of connectedness are shown in the intuitive network diagram.

Our findings provide new information for investors who have an interest in investment or hedging strategies in cryptocurrencies.

The thesis is structured as follows: Section 2 contains literature review, section 3 undergoes the methodology details, section 4 introduces the data, reports the empirical results and robustness check, and discuss the main findings and section 5 provides the conclusion.

2 Literature Review

Our work is essentially associated to the literature on the spillover index approach and its variants which was defined in papers by Diebold and Yilmaz.

Based on the vector autoregressive (VAR) model, Diebold and Yilmaz (2009) have used the spillover index approach to analyze the 19 global equity markets where they found evidence of divergent behavior in the dynamics of return and volatility spillovers.
For the variance decomposition calculation, it was based on the Cholesky factor identification of Sims (1980) which assures that the sums of forecast error variance contributions are unity. However, this method is sensitive to ordering.

In order to overcome the limitation of the forecast variance decomposition, Diebold and Yilmaz (2012) have enlarged the spillover index framework by using the generalized variance decomposition (GVD) framework of Koop et al. (1996) and Pesaran and Shin (1998) which is independent of ordering, i.e., the ordering of the variables in the VAR does not matter.
This method is useful when we have a large number of data for which it is unnecessary to specify a structural VAR model.
However, this comes at a cost, because the shocks are not necessarily orthogonal in the GVD environment (the error terms may be correlated).
Therefore, the sums of forecast error variance contributions are not necessarily unity i.e., the row sums of the variance decomposition matrix are not equal to one.
For that reason, they had divided each row in that matrix by the row sums to make the sums of forecast error variance contributions unity.

Based on this model, Diebold and Yilmaz (2014) worked on the network topology of variance decompositions in order to measure the connectedness of financial firms, they have proposed a population connectedness measure to estimate network connectedness which is built based on the variance decomposition matrix. In other words, the variance decomposition matrix of the forecast error variance decompositions is interpreted as the adjacency matrix of a directed network.

Thus, Diebold and Yilmaz (2014) revealed that the variance decomposition could be defined as weighted, directed network and that is in order to relate these new measures of connectedness to the standard key measures of connectedness in the network literature.

This population connectedness is used in this thesis to track both the average and daily time-varying connectedness of 13 major U.S. financial institutions' stock return volatilities and presented their connectedness in network diagrams. For the variance decomposition calculation, it was based on the Cholesky factor identification and the generalized identification.

Since Cholesky factor is sensitive to ordering, the constructed network allows ranking the firms by their systemic importance, where the total connectedness is often more robust to Cholesky ordering. However, the directional connectedness is sometimes more sensitive to it.
For this reason, they have found that it is better to construct the network based on the generalized variance decomposition (GVD).

The literature on cryptocurrencies has seen a surge recently. A good overview is given by Elender et al (2016).

Some researchers have focused on examining the evolution of cryptocurrencies as it has been characterized by a bubble-like behavior and extreme volatility.
For example, Kjaerland et al (2018) analyze bitcoin's price dynamics using classical time series models.

Hafner (2020) employed recursive unit-root type bubble tests, proposed initally by Phillips et al (2011) and Phillips et al (2015), extended to the case where volatility varies over time. This was then applied to 11 of the largest cryptocurrencies and the CRIX index. And the results confirm the presence of bubbles, but much less clear than under constant volatility.

The importance of investor sentiments for crypoassets has been emphasized by Chen et al (2018). Chen and Hafner (2019) defined a way to test for speculative bubbles based on StockTwits sentiment indices, see also Nasekin and Chen (2018). The latter is used as a transition variable in a soft transition autoregression. After applying the model to the CRIX index, they found that the explosive price dynamics detected locally is closer to the notion of a speculative bubble motivated by exuberant sentiment.
Their results also indicate that volatility increases as the sentiment index decreases, commonly referred to as leverage.

Since our work is primarily related to the controversial subject of Bitcoin and cryptocurrency market, we focused on the articles related to that.
Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) have used the spillover in-

dex approach to investigate the relation across three of the most popular cryptocurrencies (Bitcoin, Ripple, and Litecoin) and a variety of standard financial assets (gold, stock, SP500). Their results prove a relative isolation of these three popular cryptocurrencies from the standard assets. As a consequence, this may offer diversification benefits for investors with short investment horizons.

Moreover, Fry and Cheah (2016) have developed a model for financial bubbles and crashes and that was based on statistical physics and mathematical finance, where the goal was to measure the spillover effects.
The results indicate empirical evidence of negative bubbles in cryptocurrency markets. These evidences suggest that there is a spillover from Ripple to Bitcoin that aggravates the recent price falls in Bitcoin. The main conclusion is that Ripple is over-priced relative to Bitcoin over the period in question.

We see that most of the studies focus on the relations of cryptocurrencies to other shocks. However, only few papers pay attention to relations between different cryptocurrencies. Shuyue Yia,, Zishuang Xua,, Gang-Jin Wang (2018) applied the spillover index and its variants on the volatility connectedness in the cryptocurrency market. They have examined the static and dynamic volatility connectedness across eight different cryptocurrencies.
And in order to examine the network connectedness on a large number of data (52 different cryptocurrencies), they have used LASSO-VAR to estimate the high-dimensional vector autoregressive model.
For variance decomposition, they followed Diebold Yilmaz (2014) paper, where they have used the generalized variance decompostition framework of Koop et al. (1996) and Pesaran Shin (1998), and because $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$, they had to normalize each entry of the generalized variance decomposition matrix by the row sum, to make the variance shares do add to 1.
Their results indicate that the chosen cryptocurrencies are interconnected and the cryptocurrencies with the highest market capitalization are the ones that are more likely to propagate volatility shocks to others.
It is remarkable that Bitcoin is not the dominant player of volatility connectedness in the cryptocurrency market and that some cryptocurrencies are significant transmitters of volatility connectedness and that they even have a larger contribution of volatility spillovers to others.

Based on these papers, essentially on the Shuyue Yia,, Zishuang Xua,, Gang-Jin Wang (2018) and Diebold and Yilmaz (2014) papers , and based on the vector autoregressive(VAR) model and the spillover index approach, we are interested in investigating the static connectedness among 39 various cryptocurrencies based on the NVT ratio.

For the variance decomposition, we use another method which is Independent Componenet Analysis (ICA) rather than the generalized variance decomposition framework of Koop et al. (1996) and Pesaran and Shin (1998). This method will be more effective since it enables the identification of the underlying independent shocks, also called structural shocks, and it does not depend on the ordering of the VAR elements.

Its fundamental difference to the other methods used before, is in the assumption of non-Gaussianity, which enables us to find the original components that are stochastically independent from each other.
In our case, the method is justified by the fact that all of our shocks are significantly non-Gaussian.

In the analysis of high-dimensional data (in our sample, including 39 cryptocurrencies), we exploit the least absolute shrinkage and selection operator (LASSO) method to reduce dimensionality and shrink the sample when estimating VAR parameters

3 Methodology

3.1 VAR

The vector autoregressive model is used to investigate the relationship between various quantities. In our case, we want to capture the relationship between different cryptocurrencies.

This model generalizes the univariate autoregression model (AR) by allowing multi-variate time series.

It works like the AR model, as it defines for each variable an equation modelling its evolution over time. But instead of including only the lagged values of the variable and the error term in each equation, it also includes the lagged values of other variables.

What is remarkable in the VAR model is that it does not require knowing the variables that influence the target variable, on the contrary, it only needs a list of variables that we assume that they influence each other over time.

This VAR model is characterized by its order, which is the number of previous periods the model will use.
For our model, we used a third-order VAR which refers to a VAR model that includes lags for the last three time periods, in other words, it will model each day's NVT value as a linear combination of the last three days values.

We model here the NVT $y_{it}, i = 1, \ldots, N$ via a third order vector autoregressive model (VAR) of the form

$$y_t = \mu + \sum_{j=1}^{3} A_j(y_{t-j} - \mu) + \varepsilon_t \tag{3.1}$$

where ε_t is an error term and A_j are $N \times N$ parameter matrices.

The error terms must satisfy three conditions:

$E(e_t) = 0$, Every error term has mean of zero

$E(e_t e_t') = \Omega$, The covariance matrix of the error terms are KxK positive semi-definite matrix denoted Ω.

$E(e_t e_{t-k}') = 0$, For any non-zero K. There is no serial correlation in individual error terms, i.e., there is no correlation across time.

The model should also be stable, i.e., all the eigenvalues of the matrix A are less than one in absolute value.

VAR could be used to generate outstanding baseline forecasts, but in practice, researchers mostly use VAR models to study the effects of movements in one variable on movements in another one to reveal something about the nature of how these assets move together (or not).

3.1.1 The VAR order:

To determine the true lag order for the model, which yields the best results, as Lutkepohl (1991) pointed out that selecting a higher order lag length than the true lag lengths increases the mean square forecast errors of the VAR and selecting a lower order lag length than the true one, usually causes serial correlated errors.

There are several statistical information criteria for selecting a lag length such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), final prediction error (FPE), and Hannan-Quinn Information Criterion (HQC).

Usually, the AIC is preferred over other criteria, due to its favourable small sample forecasting features. The BIC , HQ, and FPE however, work well in large samples and they are consistent estimators of the true order.

3.2 LASSO

For large N, there would be too many parameters to estimate for reasonable sample sizes.

This heavy parameterization is the major drawback of the VAR as it limits its applicability because while estimating such a highly parameterized system, it will provide a high degree of fit to the data. Hence, the forecasts can be very poor in terms of mean square error.
Thus, an urgent problem that needs to be addressed, is how to estimate VAR parameters in a high-dimensional environment.

To tackle this issue where restrictions are necessary for A_j, one can use techniques such as LASSO that can select a subset of variables among all the possible ones, which can reduce the parameter space greatly.

LASSO approach is performed with the aim of identifying the value of the parameter that corresponds to the best generalization.
In general, this process implies the same regression equations as the original model. Yet, a penalty is added to the LS loss function when estimating the parameters, to shrink some of them to zero.
This penalty is equal to the sum of the absolute values of all or a subset of the parameters. If the feature is irrelevant, LASSO penalizes its coefficient and make it zero.
Hence, the features with a coefficient equal to zero are removed and the rest are taken.

The impact of the penalty can be varied by multiplying it by a tuning parameter. If the tuning parameter equals to zero, the LASSO VAR(p) model reduces to the standard VAR(p) model. And the larger the tuning parameter, the more parameters will be forced to be zero.

To free the user from this delicate task, a cross-validation technique in the training set was performed. Specifically, five-fold cross-validation (CV) is used.
For instance, if information criteria suggest to choose a lag order of $p = 3$. We then estimate the model by minimizing equation by equation the following LASSO criterion

$$\sum_{t=1}^{T} \varepsilon_{it}^2 + \lambda_i \sum_{j=1}^{N} \sum_{k=1}^{3} |A_{ijk}|$$

with respect to the coefficients A_{ijk}, where the tuning parameters λ_i is chosen by five-fold cross-validation.

3.3 Variance Decomposition

In the following, we study the implications of the estimated parameters for the decompositions of the variances of forecast errors, in the spirit of Diebold and Yilmaz (2014), which allows us to quantify the network relationships between cryptocurrencies.

3.3.1 ICA

It is important to have an orthogonal system, as it makes the calculation of the variance decomposition easy, and it ensures that the variance of a weighted sum is equal to a weighted sum of variances.

However, shocks are often non-orthogonal. For that reason, we have to identify uncorrelated structural shocks from the correlated shocks we have.

The Cholesky-factor vector autoregression(VAR) identification popularized by Sims is quite used, but this method may be sensitive to ordering. Although it is found that total connectedness is often robust to Cholesky ordering, directional connectedness is sometimes more sensitive to it.

For this reason, in order to make the innovations independent or as independent as possible, and using a method that is independent of order, we chose to use the independent component analysis (ICA) method which aims to find a linear representation that seems to capture the essential structure of the data under non-Gaussianity.

To find this transformed error term u_t, we need to find the linear combination v of the error term ϵ_t ,which is written is the equation below:

$$u_t = V * \epsilon_t$$

such that $cov(u_t) = I$, where I is the identity matrix.
Thus,all rows of the transformed matrix u_t are uncorrelated.

So, we can perform a variance decomposition for our multivariate model using ICA, since it can deal with a high number of dimensions, and it can only be applied when there is no identification problem, which means having independent residuals with non-Gaussian distribution.

Thereby, a pre-processing need to be performed before applying the ICA to get an optimal estimate of the independent components.

Suppose our model is written as

$$y_t = Ay_{t-1} + \epsilon_t$$

where ϵ_t is the error term of the model. These shocks are correlated with each other, and they should have non-gaussian distribution to be able to use ICA.

The first pre-processing step is centering the data, where we subtract the mean from the input, and it is used to simplify the ICA calculation.

$$\epsilon_{i,centered} = \epsilon_t - mean(\epsilon_i)$$

where $\epsilon_{i,centered}$ is the centered matrix, and $cov(\epsilon_{i,centered}) = cov(\epsilon_i)$

The second step, is to whiten the shocks which means that we are going to orthogonalize them in order to remove any correlation in the error terms.

This whitening process will restore the initial shape of the error terms as it is a linear transformation of coordinates of the observed residuals.

The standardization of shocks u_t is defined as

$$\tilde{u}_t = \Sigma^{-\frac{1}{2}} \epsilon_{t,centered}$$

where Σ is the variance-covariance matrix of ε_t and $\Sigma^{-1/2}$ is the inverse of the symmetric square root of Σ.

As a result, these $\tilde{u}_t$ are "pre-whitened" in the sense that their mean is zero and variance-covariance equal to the identity matrix.
And they are only independent under Gaussianity, which means that these innovations are identified under non-Gaussianity of ε_t.

In order to obtain these orthogonalized shocks $\tilde{u}_t$, we need to compute $\Sigma^{-1/2}$, which requires the use of eigenvalue decomposition, where $\Sigma^{-1/2}\Sigma^{1/2} = I$.

The decomposition is as following:

$$\Sigma^{-1/2} = \Gamma\Omega^{-1/2}\Gamma^t$$

where Γ is the matrix of eigenvectors and Ω is a diagonal matrix containing the eigenvalues.

After doing the pre-whitening, we extract structural innovations by Independent Component Analysis (ICA), which uses an orthogonal rotation matrix R, called the mixing matrix, given by the ICA algorithm to rotate $\tilde{u}_t$ such that:

$$u_t = R\tilde{u}_t$$

where the components of u_t are maximally independent, which means that the covariance of the transformed matrix is equal to the identity matrix.

Therefore,

$$u_t = \Sigma^{-1/2} R \epsilon_t$$

The ICA will only have to rotate the resulting matrix with the aim of turning it back to the original axis space, in other words, this will re-project the whitened matrix into the original space.

This rotation is performed by minimizing the gaussianity of the projected data in order to recover the original sources which are statistically independent.

The rotation matrix is found by FastICA which identify independent shocks in a unique way. FastICA is an efficient and popular algorithm used for Independent Component Analysis, invented by Aapo Hyvärinen.

Like most ICA algorithms, FastICA seeks an orthogonal rotation of pre-whitened data, through a fixed-point iteration scheme, that maximizes a measure of non-Gaussianity of the rotated components. Thus, it identifies independent shocks in a unique way.

3.3.2 Forecast Error Variance Decomposition

First, if we consider the lag order is 2, then starting from the reduced form VAR(2) model in (3.1), we may obtain the infinite order VMA representation,

$$y_t = \sum_{j=0}^{\infty} \Phi_j \varepsilon_{t-j}$$

with coefficient matrices Φ_j that, for our VAR(2) model, can be obtained recursively as $\Phi_0 = I_N$, $\Phi_1 = A_1$, $\Phi_2 = \Phi_1 A_1 + A_2, \dots, \Phi_j = \Phi_{j-1} A_1 + \Phi_{j-2} A_2, \dots$, see e.g. Lütkepohl (2005).

Rewrite the model as

$$y_t = \sum_{j=0}^{\infty} \Theta_j u_{t-j}$$

where $\Theta_j := \Phi_j \Sigma^{1/2} R'$ and $u_t \sim (0, \Sigma)$

All aspects of connectedness are contained in this representation: where the contemporaneous aspects of connectedness are explained by Θ_0 and the dynamics ones is summarized by the other coefficients (Θ_1, Θ_2,..).

And because we have a lot of coefficients, this may make it difficult to unfold the connectedness. So, it was found that it is better to transform them to more compactly summarizes connectedness. This is achieved by variance decomposition.

The proportion of the h-step ahead forecast error variance of crypto i accounted for by innovations in crypto j is then given by

$$\omega_{ij,h} = \sum_{k=0}^{h-1} \theta_{ij,k}^2 / \sum_{j=1}^{N} \sum_{k=0}^{h-1} \theta_{ij,k}^2$$

where $\sum_{j=1}^{N} \omega_{ij,h} = 1$ by construction.

Variance decomposition enables us to determine how much of the variability in the selected variable is lagged by its own variance. In addition, it shows us which of the independent variables is "stronger" to explain the variability of this variable.

3.4 Network Connectedness

This analysis can be refined following Diebold and Yilmaz (2014) by viewing variance decompositions as weighted directed networks.

	x_1	x_2	...	x_N	From Others
x_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\Sigma_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\Sigma_{j=1}^N d_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	$\cdots$	d_{NN}^H	$\Sigma_{j=1}^N d_{Nj}^H, j \neq N$
To Others	$\Sigma_{i=1}^N d_{i1}^H$ $i \neq 1$	$\Sigma_{i=1}^N d_{i2}^H$ $i \neq 2$	$\cdots$	$\Sigma_{i=1}^N d_{iN}^H$ $i \neq N$	$\frac{1}{N}\Sigma_{i,j=1}^N d_{ij}^H$ $i \neq j$

Figure 3.1: Connectedness table Schematic

This connectedness table explains different connectedness measures and their relationships. The upper left NxN block contains the variance decomposition matrix where they denote it $D^H = [d_{ij}^H]$.

The total directional connectedness measures are defined by the off-diagonal row which is labeled "from others" containing the column sums, and by the off-diagonal column which is labeled "to others" containing each column row sums.

For instance, if we take the first row, the sum of its off-diagonal elements gives the share of the H-step forecast-error variance of that variable coming from shocks arising in other variables.

Each element of the variance decomposition matrix $\omega_{ij,h}$ measures the pairwise directional connectedness from j to i

$$C^H_{i\leftarrow j} = [\omega_{ij,h}]$$

Since our variance decompostion matrix is not symmetric , $C^H_{i\leftarrow j} \neq C^H_{j\leftarrow i}$ Therefore, we have $N^2 - N$ different pairwise directional connectedness measures.

The "to" measure is defined as the total direction connectedness to others from j, which measures the sum of the contributions of crypto j to all other cryptos' forecast errors, and it can be viewed as a "to"-degree of a node (i.e. a crypto) of the network.

$$C^H_{\cdot\leftarrow j} : \omega_{\cdot j} = \sum_{i=1, i\neq j}^{N} \omega_{ij}$$

Likewise, the "from" directional connectedness is defined as the total direction connectedness from others to i, which measures the sum of the contributions of all other cryptos j to explain the forecast error variance of crypto i.

$$C^H_{i\leftarrow \cdot} : \omega_{i\cdot} := \sum_{j=1, j\neq i}^{N} \omega_{ij}$$

Therefore, we have $2N$ total direction connectedness measures, where N measures explain the transmitted shocks to others and the other N measures explain the received shocks from others.
Consequently, the net total direction connectedness is equal to

$$C^H_i = C^H_{\cdot\leftarrow i} - C^H_{i\leftarrow \cdot}$$

where there is $\frac{N^2-N}{2}$ net pairwise direction connectedness measures.

where we have N net total directional connectedness measures.

Finally, the total connectedness measure for the network of cryptos is the grand total of the off-diagonal elemetns in the variance decomposition matrix, which is given by $C^H : \omega = \sum_{i=1}^{N} \omega_{i\cdot} = \sum_{j=1}^{N} \omega_{\cdot j}$,
This total connectedness extract the most important aspect of the system, and it corresponds to the mean degree of the network. The larger the mean degree,

the greater the overall network connectedness.

Therefore, this connectedness table may reveal a lot of important information, as it may reveal how various variables connect to a specific variable($C^H_{i\leftarrow j}$), how all variables in the system connect to it ($C^H_{i\leftarrow \cdot}$), how to identify important variables in the system that lead to a large total directional connectedness to others, and finally, it reveals the total connectedness of the system(C^H_i)

4 Data and Empirical Analysis

In the first step, for this empirical analysis, data was collected from the CoinMetrics website, There are more than 4000 cryptocurrencies by January 2021, we firstly selected 100 cryptocurrencies from the top 500.

On the basis of these 100 assets, we excluded the ones started after 2018.
We chose to start from 2018 for two reasons; first, we have some cryptocurrencies that are in the top 40 by market capitalization but started late, naming a few: Huobi Token (ht), Synthetix (snx), Crypto.com Coin(cro)... And second, we wanted to have a large sample length that could make our analysis more convincing.

Hence, we have reduced the dataset of cryptocurrencies to the two-year period between 11.11.2018 and 16.02.2021 which was extracted by joining all the cryptocurrencies together to match the number of observations and dates of all these assets.

Also, we took out the ones that disappeared after a while since cryptocurrencies emerge and disappear continually. Moreover, we removed cryptocurrencies with consecutive missing values higher than ten days.

In order to make our analysis more reliable, our selected sample included different tier currencies by market capitalization, Bitcoin, Ethereum, Tether whose market capitalizations stay in the world's top five cryptocurrencies, are "top-tier" cryptocurrencies.

Zcash(zec), Basic Attention token(bat) and bitcoin gold(btg) are "second-tier" cryptocurrencies, representing "middle cryptocurrency" in terms of market capitalization.

Aelf and Gas are two cryptocurrencies with small market capitalization representing "minor cryptocurrency", which ranked 266th and 355th by market cap.

In Table 1, we report these 39 cryptocurrencies' symbols, market capitalizations (MCs) and rankings of MCs.

Hence, we extracted 39 cryptocurrencies of the 500 largest cryptocurrencies by market capitalizations which have been publicly traded for at least two consecutive years and whose NVT Adjusted ratio is provided by the CoinMetrics website.

Table 4.1: The 39 cryptocurrencies with their symbols, market capitalizations (MCs) and rankings by MCs

Cryptocurrency	**Symbol**	**MC**	**Rank by MC**	**Cryptocurrency**	**Symbol**	**MC**	**Rank by MC**
Bitcoin	Btc	894.52B	1	**Basic Attention Token**	bat	1.54B	62
Ethereum	eth	194.55	2	**Bitcoin gold**	Btg	1.38B	68
Tether	usdt	36.81B	4	**Decentraland**	mana	1.25B	73
XRP	xrp	36.25 B	5	**0x**	zrx	1.14B	79
Cardano	Ada	32.06B	6	**Waves**	waves	1.11B	82
Litecoin	ltc	12.39B	9	**OMG Network**	omg	1.09B	83
Chainlink	link	12.39B	10	**DigiByte**	dgb	997.39M	85
Bitcoin Cash	Bch	9.79 B	12	**Ren**	ren	852.71M	95
Stellar	Xlm	9.15B	13	**Lisk**	lsk	656.1M	107
USD Coin	usdc	9.12B	14	**Verge**	xvg	617.18M	112
Doge Coin	Doge	6.60B	19	**Kyber Network**	knc	559.03M	114
Tezos	Xtz	3.71B	30	**Augur**	Rep	433.27M	129
Neo	neo	3.58B	32	**Status**	snt	434.27M	130
Nem	Xem	3.01B	38	**Aragon**	ant	371.61M	139
Huobi Token	ht	2.59B	42	**FunToken**	fun	377.87M	141
Dash	dash	2.17B	46	**Civic**	cvc	312.03M	148
Decred	dcr	1.99B	49	**Gnosis**	gno	204.16M	187
Ethereum Classic	etc	1.79B	54	**Aelf**	elf	180.24M	266
Maker	mkr	1.75B	58	**Gas**	gas	109.95M	355
Zcash	Zec	1.68B	59				

Using these various cryptocurrencies would make our analysis more reliable and help to asset diversification for investors.

In Figure 1 below, we show the daily NVT-Adjused series of nine cryptocurrencies.

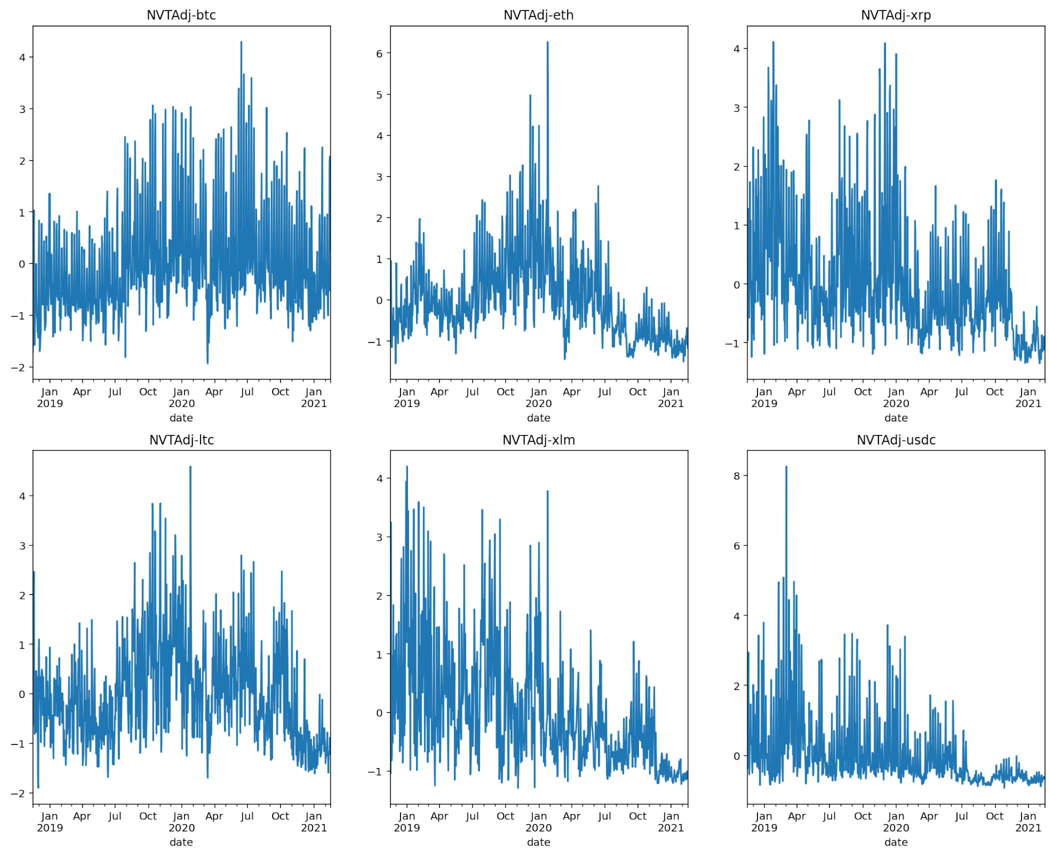

Figure 4.1: Evolution of NVT ratio over nine cryptocurrencies from November 2018 to February 2021

We first started by checking if there are any missing values.
Among these 39 cryptocurrencies, we found that there are 38 without data loss (data records are available for daily transactions), we only have Verge(xvg) that are missing one data, so we imputed the missing value.

We show in Table 2, the descriptive statistics of the daily NVT series for all the 40 cryptocurrencies during the entire period.

Table 4.2: NVT descriptive statistics for the 39 cryptocurrencies during the period from 15 November 2018 to 16 February 2021

	Count	Mean	Std	Min	25 %	50 %	75 %	Max	Skewness	Kurtosis
btc	825.0	80.25	29.48	23.28	59.79	73.86	91.54	206.74	1.23	1.43
eth	825.0	53.17	29.07	8.29	32.38	47.19	67.02	235.29	1.44	3.75
usdt	825.0	22.20	15.63	2.11	11.27	17.91	28.55	99.53	1.51	2.58
xrp	825.0	252.09	177.23	12.74	127.82	207.67	321.87	980.55	1.35	1.86
ada	825.0	56.89	48.32	0.34	28.03	50.46	75.36	946.67	7.97	138.87
ltc	825.0	110.71	55.39	5.44	68.37	103.65	145.87	364.93	0.92	1.19
link	825.0	361.88	405.27	9.92	119.66	230.08	430.18	2804.90	2.81	9.68
bch	825.0	48.45	32.31	4.88	26.69	39.47	62.58	194.21	1.26	1.53
xlm	825.0	1143.88	886.99	1.71	487.11	899.69	1579.80	4867.69	1.33	1.86
usdc	825.0	10.84	11.44	0.23	3.90	6.81	13.17	105.25	2.74	10.58
doge	825.0	91.60	45.61	4.35	58.92	85.71	120.36	253.17	0.60	0.20
xtz	825.0	193.08	154.74	21.76	88.13	146.59	251.98	1289.07	2.13	7.16
neo	825.0	35.39	44.26	0.26	9.87	21.13	38.90	332.42	3.04	11.07
xem	825.0	504.06	410.31	0.00	228.48	402.31	649.58	3132.43	1.98	5.85
ht	825.0	7722.28	96225.33	1.14	380.07	1039.16	2769.06	2722436.69	27.38	771.56
dash	825.0	112.00	44.76	9.91	81.58	107.30	139.50	280.52	0.58	0.70
dcr	825.0	116.34	59.46	7.77	71.56	115.46	158.69	317.98	0.18	-0.50
etc	825.0	169.62	269.47	8.70	52.77	97.60	175.90	4237.99	6.70	73.40
mkr	825.0	248.43	262.08	3.20	67.45	162.06	341.62	1924.67	2.23	6.96
zec	825.0	41.15	17.81	10.64	28.58	38.00	50.17	148.20	1.29	3.03
bat	825.0	144.91	137.55	0.97	53.43	105.80	191.73	1318.59	2.70	12.66
btg	825.0	411.14	330.71	4.34	170.97	332.95	560.03	2414.00	1.78	5.17
mana	825.0	286.67	351.16	3.18	76.63	172.90	369.34	4420.86	4.22	32.57
zrx	825.0	196.71	163.45	5.86	88.08	149.08	255.28	1257.77	1.89	4.96
waves	825.0	365.64	430.56	6.16	119.47	242.23	453.57	6238.69	5.18	51.25
omg	825.0	127.62	121.34	3.23	51.77	94.63	165.41	1515.64	3.58	26.60
dgb	825.0	211.01	99.37	23.71	140.44	201.46	268.23	639.98	0.68	0.65
ren	825.0	257.72	525.22	4.10	48.65	132.48	314.22	11441.70	13.24	257.85
lsk	825.0	297.04	231.66	8.89	137.36	242.36	393.74	2005.72	2.05	7.36
xvg	825.0	142.85	599.49	7.86	47.52	72.33	123.52	15095.37	21.26	498.96
knc	825.0	89.71	85.79	3.10	33.86	62.38	115.17	681.23	2.35	8.04
rep	825.0	464.98	911.11	1.41	79.53	192.56	464.04	9687.33	5.54	40.05
snt	825.0	384.21	509.45	3.79	128.08	231.05	426.17	4678.64	4.24	24.16
ant	825.0	1275.70	2112.15	3.17	229.65	616.13	1449.49	27928.65	5.35	44.54
fun	825.0	289.01	261.46	2.94	102.57	221.10	390.77	2088.93	1.92	5.52
cvc	825.0	330.02	577.22	2.26	56.29	161.94	376.69	10368.75	8.30	119.02
gno	825.0	16697.42	27369.76	1.17	2891.66	7221.86	18458.58	311478.58	4.51	30.74
elf	825.0	246.87	436.76	1.50	61.33	121.33	244.91	5458.71	6.08	52.99
gas	825.0	38.10	49.55	0.05	5.15	19.45	51.58	361.79	2.32	6.72

We see that each NVT series comprises 825 observations.
We observe a remarkable gap between mean and median for some of the time series which indicates that the data are skewed, or that it may be due to the presence of outliers in the data.

For instance, we have for Huobi Token (ht) time series, the mean is equal to 7722.28 while the median is equal to 1039.16. This huge difference may suggest checking the existence of outliers in the data.

We would like to also highlight the enormous difference between the median for each cryptocurrency, we take the example of USD Coin(usdc) and Stellar (xlm), where they have median values equal to 6.81 and 899.69, respectively. This may affect the coefficients results later. For this reason, we found out that it is better to standardize our data.

Apart from Bitcoin, and other altcoins, most of the cryptocurrencies have very high excess kurtosis as the market for altcoins is still developing.

Moreover, we can observe from this summary that Bitcoin, ethereum, Tether(usdt), USD Coin (usdc), Bitcoin cash(bch),and Zcash (zec) have the lowest volatility compared with other cryptocurrencies, their volatility shows that they move comparatively slight.
This is because these cryptocurrencies are more stable than the others, and there are more market participants who believe in it.

Furthermore, we have Tether(usdt) which is The first cryptocurrency to be secured by the U.S. dollar, and USD Coin (usdc) which are called stablecoins which means that these cryptocurrencies are meant to limit the volatility that investors experience when using these cryptos and that is by securing its value to another asset, including fiat currencies, such as US dollars (USD). Therefore, these stablecoins have minimal volatility.

However, we see that the volatility of the series Huobi Token (ht), Synthetix (snx), Augur (rep), Aragon (ant) and Gnosis (gno) is too high compared to the other cryptocurrencies, which means that NVT values move aggressively up or down daily.

We have encountered some outliers, which were detected by checking whether any point falls above the 6 sigma rule.
In the figure below, we show how we detected the outliers, where we took the example of two time series.

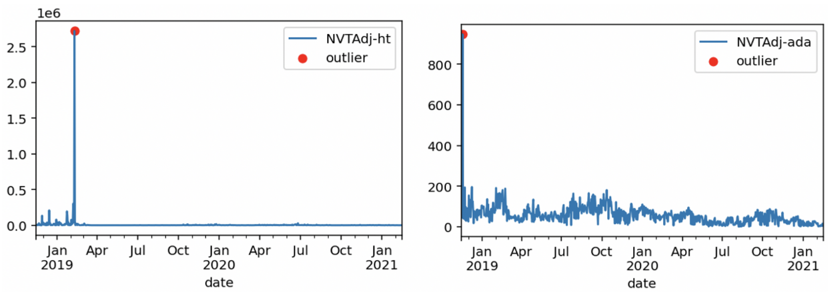

Figure 4.2: Detection of outliers for Huobi Token (ht) and cardano (ada) series

In these graphs, the circled data points are recognized to be outliers.
Therefore, in order to remove these outliers, we replaced them with the 3 sigma rule.

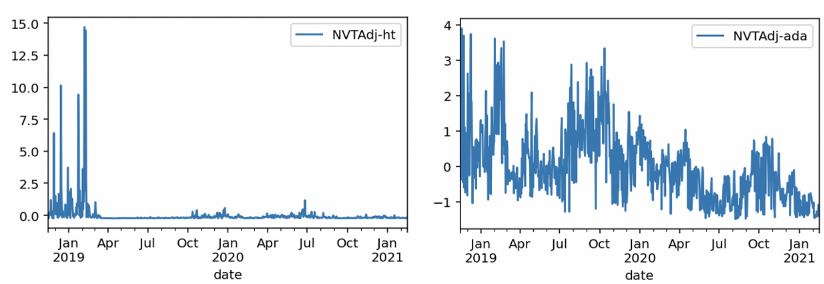

Figure 4.3: Treatment of outliers for Huobi Token (ht) and cardano (ada) series

After treating the remarkable outliers from some time series, we see that the scale is now similar for all these time series.

Moreover, we have checked the correlation between these various cryptocurrencies.
In the figure below, we show the correlation between the different cryptocurrencies based on their NVT ratio.

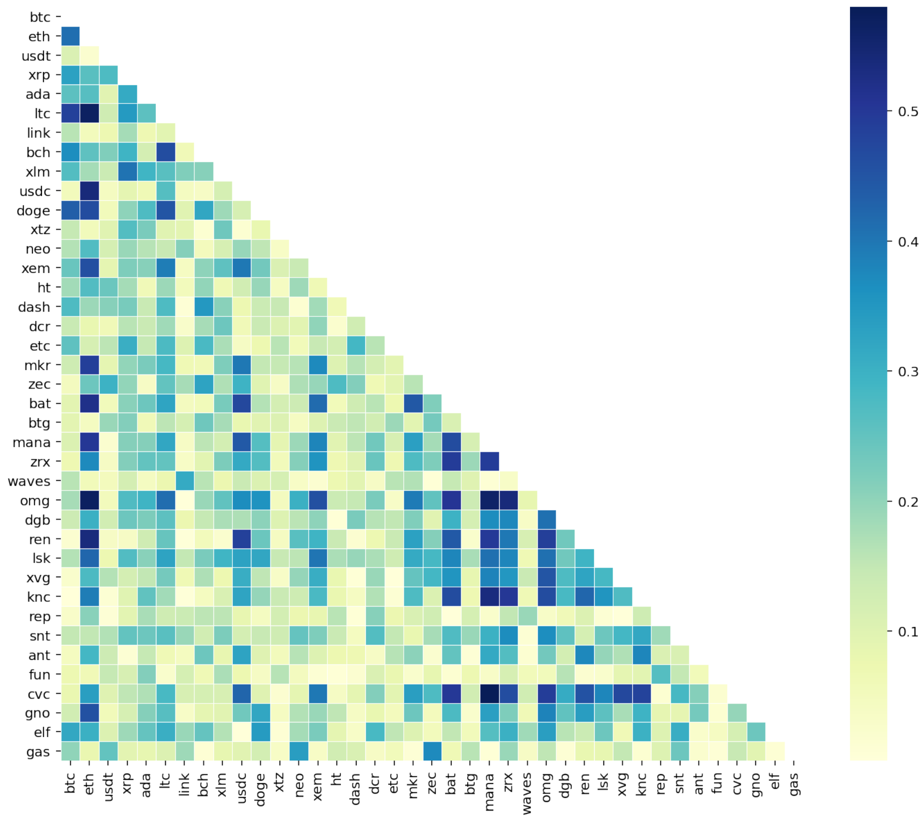

Figure 4.4: Correlation between different cryptocurrencies based on NVT ratio

Since we have ordered the cryptocurrencies by market capitalization, we see from this heatmap that most of the cryptocurrencies with the highest market capitalization, such as bitcoin, ethereum, Ripple(xrp, Cardano(ada), Litecoin (ltc), Chainlink(link), Stellar(xlm) are correlation with each other.

Whereas, the cryptocurrencies from the "minor-cryptocurrencies" i.e. with the lowest market capitalization such as gas and elf have a very low correlation with all the other cryptocurrencies.

Moreover, we can observe that there are some cryptos from the first and second-tier which are correlated with roughly all the other assets. such as xrp, Cardano(ada), Chainlink(link), Stellar(xlm), USD Coin(usdc) from the first tier and Basic Attention Token(bat), Decentraland(mana), 0x (zrx) and OMG Network(omg) from the second one.

To detect whether or not there is seasonality in these cryptocurrencies, we have checked their autocorrelation function(ACF) which defines how data points in

a time series are related, on average, to the preceding data points.
The graph below shows different ACF plots for various cryptocurrencies. We took as an example 9 cryptocurrencies to check their ACF.

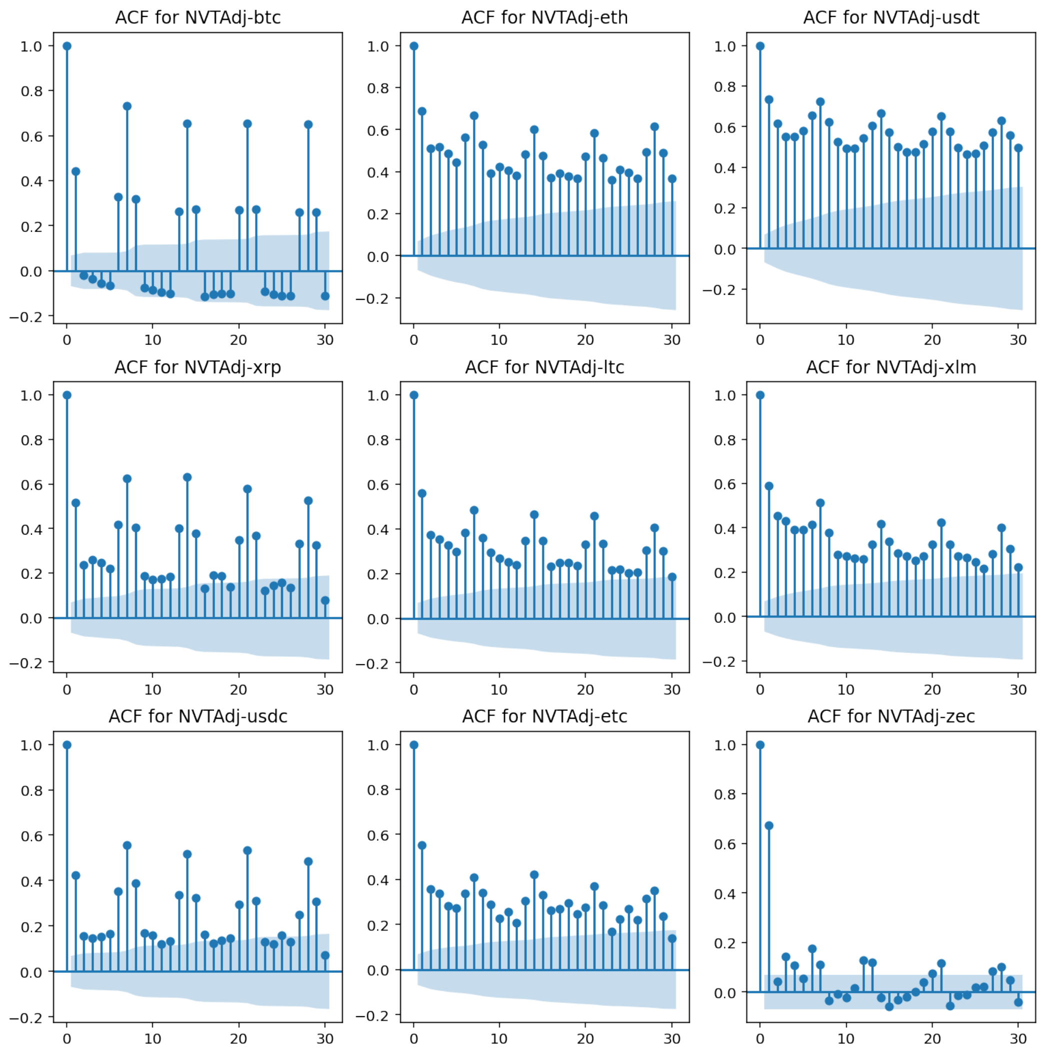

Figure 4.5: ACF plots for 9 cryptocurrencies

From these ACF plots, we can see that there is a clear seasonality in these time series.

To remove this seasonality, we use the seasonal decomposition method which breaks down the time series and then we take off the seasonal component from

it, a weekly pattern over all these time series.
The resulting time series without seasonality is in the figure below.

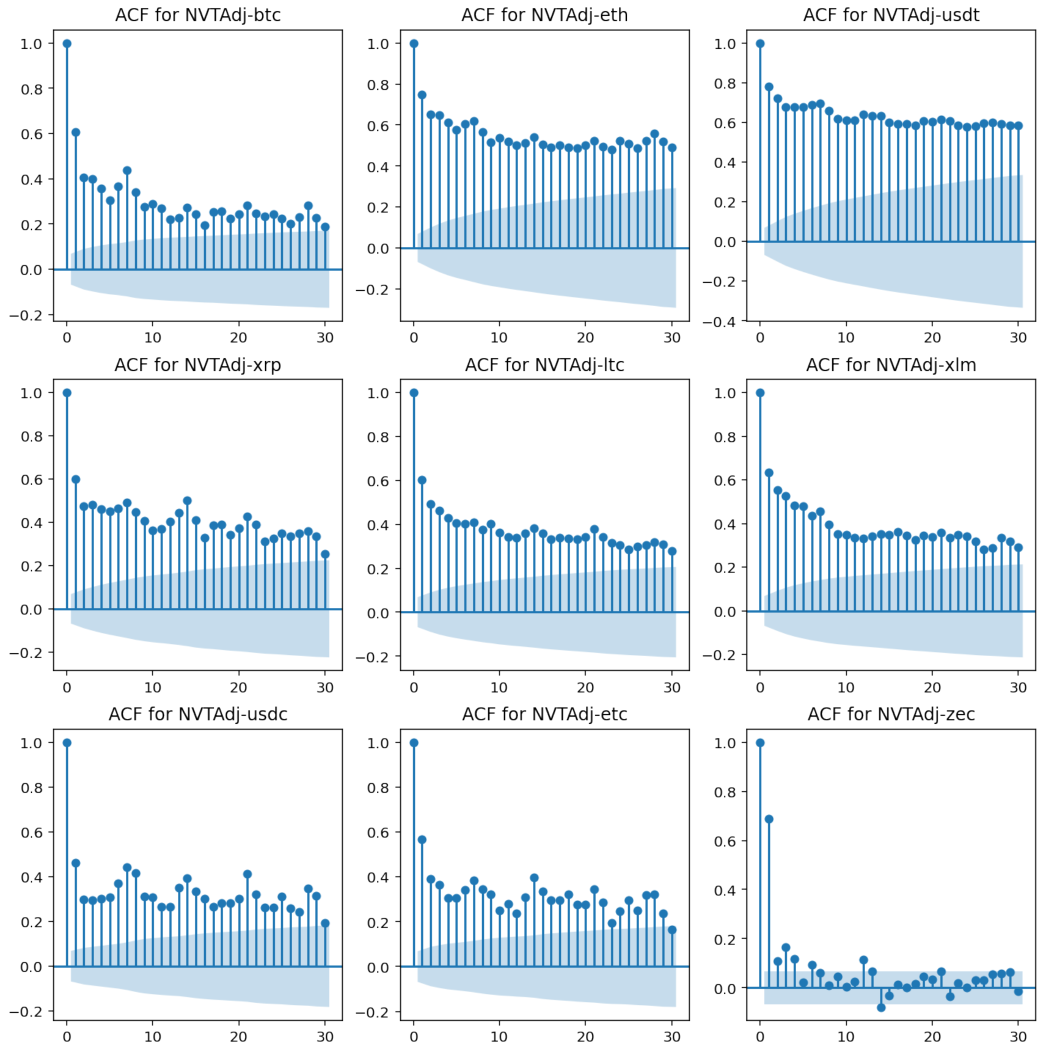

Figure 4.6: ACF plots of 9 cryptocurrencies after removing seasonality

We can see that those weekly patterns have been removed.
We have also detected some cryptocurrencies with trends, so we need to remove the linear trend along the axis from data.

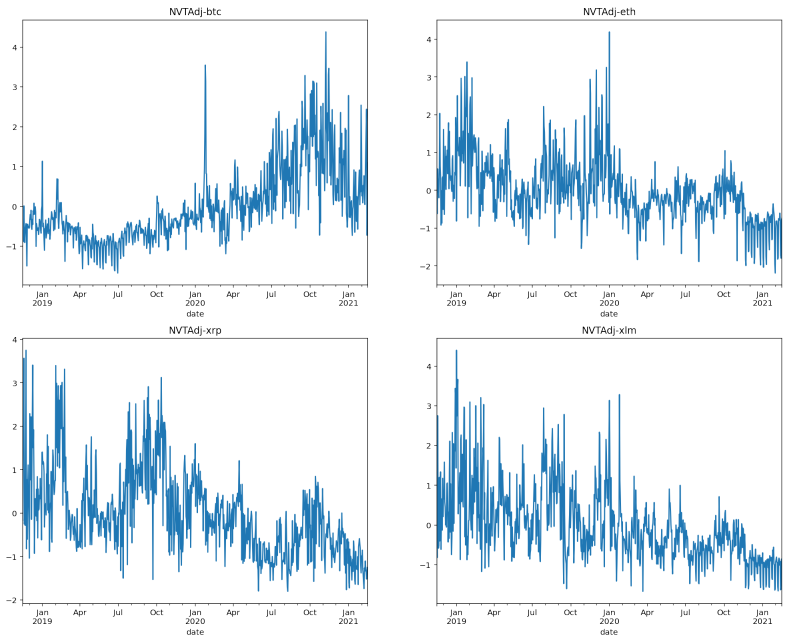

Figure 4.7: ACF plots of 9 cryptocurrencies after removing seasonality

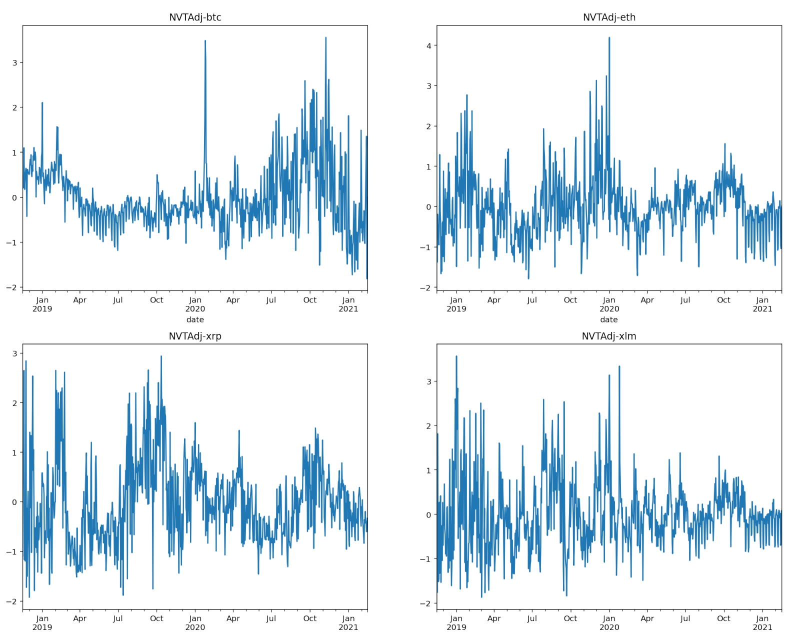

Figure 4.8: ACF plots of 9 cryptocurrencies after removing seasonality

We can observe from these graphs that the trend was removed from these series.

To analyze the co-movement of the cryptocurrencies, and since our expanded sample including 39 cryptocurrencies is a type of high-dimensional variable setting, we first try to use the traditional Vector Autoregressive model (VAR) estimation approach, then we estimate VAR using LASSO.
Afterwards, we calculate the variance decompositions and relevant network connectedness using the estimated VAR parameters.

In order to build an appropriate Vector Autoregressive model, this model comes with specific data requirements. In addition to the standard assumptions associated with linear regression models (Cohen, Cohen, West, Aiken, 2003), two assumptions pertain to the time aspect of the VAR model.

First, the time between consecutive measurements should be of equal length.
Second, the data are assumed to be stationary (requiring the data to have constant mean values, (co)variances, and autocorrelation across time, without any cycles or trends; Liu West, 2015).
Therefore, all of the 39-time series that are used in the analysis must be stationary.

We can check the unit-root structure of the data by using formal tests for that; (Dickey Fuller, 1979), Phillips-Perron test (PP) (Phillips Perron, 1998), and KPSS (Kwiatkowski, Phillips, Schmidt, Shin, 1992) are recognized as unit root tests for a time series.
We chose to apply Augmented Dickey-Fuller(ADF) in order to test unit-roots.
In the table below, we demonstrate the result of the stationarity test for each time series.

Table 4.3: Results of the ADF stationarity test, where the critical value 5% is -2.865

Time series	Test value	P-value	significance
btc	-4.97	0.0	Stationary
eth	-2.54	0.10	Non-Stationary
usdt	-3.93	0.0018	Stationary
xrp	-3.36	0.0123	Stationary
ada	-4.84	0.0	Stationary
ltc	-2.9478	0.0401	Stationary
link	-3.23	0.0179	Stationary
bch	-1.78	0.3862	Non-Stationary
xlm	-7.5075	0.0	Stationary
usdc	-2.0609	0.2605	Non-Stationary
doge	-3.28	0.0154	Stationary
xtz	-5.87	0.0	Stationary
neo	-2.81	0.0556	Non-Stationary
xem	-7.2305	0.0	Stationary
ht	-3.3504	0.0128	Stationary
dash	-6.81	0.0	Stationary
dcr	-3.94	0.0017	Stationary
etc	-2.58	0.0954	Non-Stationary
mkr	-4.94	0.0	Stationary
zec	-3.80	0.0029	Stationary
bat	-3.68	0.0044	Stationary
btg	-6.47	0.0	Stationary
mana	-2.31	0.1657	Non-Stationary
zrx	-3.37	0.0119	Stationary
waves	-5.20	0.0	Stationary
omg	-2.67	0.07	Non-Stationary
dgb	-3.21	0.0193	Stationary
ren	-4.77	0.0001	Stationary
lsk	-3.03	0.0318	Stationary
xvg	-11.53	0.0	Stationary
knc	-3.5209	0.0075	Stationary
rep	-2.3868	0.1455	Non-Stationary
snt	-2.78	0.0601	Non-Stationary
ant	-3.6019	0.0057	Stationary
fun	-5.06	0.0	Stationary
cvc	-3.77	0.0031	Stationary
gno	-2.8867	0.0469	Stationary
elf	-3.3967	0.0111	Stationary
gas	-3.7953	0.0003	Stationary

These test results indicate that not rejecting the null hypothesis of unit-root at 5 levels of significance and critical values suggest that the data is non-stationary.

Thus, we found that there are 9 variables that are non-stationary. Nevertheless, we can still run a VAR estimation using these level data.

There are many ways to get rid of the non-stationary time series problem; we might opt to use percentage change or differencing the series to make them stationary and see if that provides better results and forecasts but at the cost of ignoring possibly important (so-called "long-run") relationships between the levels.

4.1 VAR

To analyse the interaction between the cryptocurrencies in a multivariate framework, and after verifying the stationarity of these time series, we move forward into this area by applying a vector autoregressive (VAR) model which is based on the NVT ratio for our 39 cryptocurrencies.

4.1.1 The VAR order:

The order of the model is what characterizes it, which is the number of earlier time periods the model will use.

So, we need to determine the true lag order for this model, which yields the best results, as Lutkepohl (1991) pointed out that selecting a higher order lag length than the true lag lengths increases the mean square forecast errors of the VAR and selecting a lower order lag length than the true one, usually causes auto-correlated errors.

First, we based the order selection on the information criteria.
In our case, we will be using AIC criterion

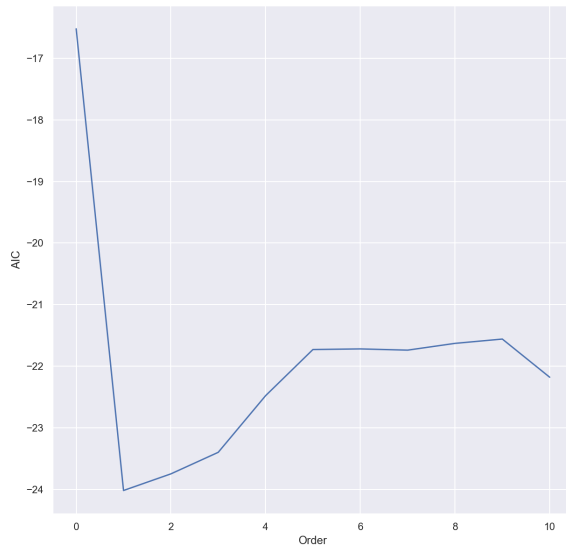

Figure 4.9: Investigating optimal order of VAR model

This graph reveals the minimum values of AIC have been got at the lag length of order one, which means that the appropriate model for our data is VAR(1). We can also check the results based on all of the information criteria as in the table below.

Table 4.4: Optimal order of VAR model

	AIC	**BIC**	**FPE**	**HQIC**
0	-16.52	-16.29*	6.714e-08	-16.43
1	-24.02*	-15.01	3.724e-11*	-20.56*
2	-23.75	-5.975	4.940e-11	-16.93
3	-23.40	3.160	7.475e-11	-13.20
4	-22.48	12.85	2.087e-10	-8.918
5	-21.73	22.38	5.320e-10	-4.798
6	-21.72	31.17	7.133e-10	-1.418
7	-21.74	39.92	1.042e-09	1.926
8	-21.63	48.82	2.040e-09	5.409
9	-21.56	57.66	4.595e-09	8.842
10	-22.18	65.82	6.641e-09	11.60

This table shows that the order of the VAR model based on AIC, FPE and HQIC is equal to one. After choosing the optimal order by these criteria, we have then tested whether there are serial correlation in the residuals.

This model failed, since we saw the presence of auto-correlated errors, which indicates that we have a lower order lag length.
For that reason, we have increased the lag order until this condition was satisfied.

Hence, we end up with a third order VAR (VAR(3)) which refers to a VAR model that includes lags, for the last three time periods, in other words, it will model each day's NVT value as a linear combination of the last three days of it.

We then visualized the resulting regression coefficients after fitting the model.

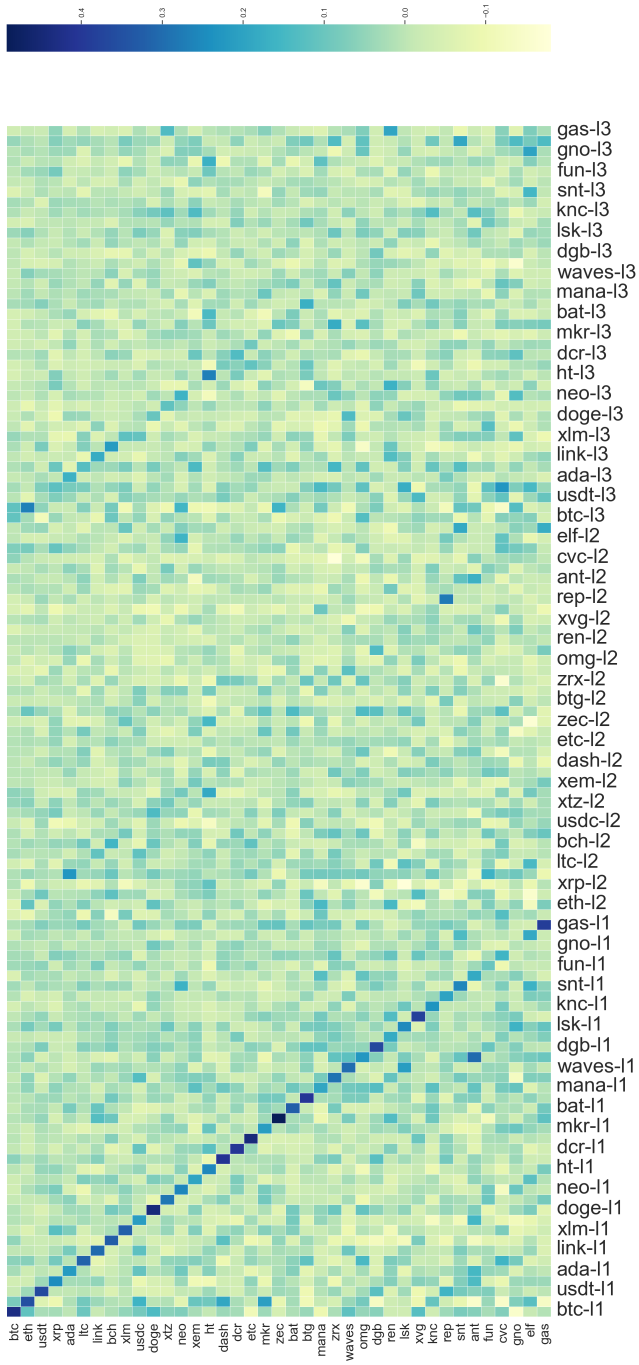

Figure 4.10: Coefficients of the VAR model

As seen in the figure above, most of the cryptocurrencies have high coefficients values for their lagged values, they are are mostly influenced by their lags. Moreover, we see that they are influenced by the lagged values of other cryptos, where some of them have high coefficients.

4.1.2 Diagnostics

After estimating a suitable VAR(3) model for the variables. This stage of the analysis deals with the diagnostic checking process.
There are several methods that control the robustness of the model and There are graphical analysis tools and statistical tests of the residuals that have been used for the diagnostic checks.

1- Autocorrelation

Our assumption is that the residuals should, as much as possible, have no serial correlation.
we need to check that the residuals are white noise, if they are, then they are uncorrelated with the previous periods.
We used for that Ljung-Box test, where the null hypothesis is having no autocorrelation.
if there are a lot of serial correlation in the data then we may have to increase the order lag length.

Table 4.5: P-values for the serial correlation test

	lag1	lag2	lag3
btc	0.963	0.957	0.989
eth	0.667	0.336	0.137
usdt	0.771	0.803	0.51
xrp	0.763	0.583	0.723
ada	0.499	0.237	0.091
ltc	0.742	0.884	0.531
link	0.42	0.491	0.311
bch	0.3	0.168	0.185
xlm	0.821	0.974	0.917
usdc	0.867	0.874	0.966
doge	0.97	0.638	0.201
xtz	0.5	0.575	0.297
neo	0.66	0.314	0.097
xem	0.709	0.829	0.897
ht	0.849	0.725	0.806
dash	0.577	0.769	0.749
dcr	0.856	0.943	0.372
etc	0.799	0.804	0.85
mkr	0.889	0.864	0.829
zec	0.798	0.909	0.565
bat	0.814	0.959	0.992
btg	0.785	0.942	0.655
mana	0.993	0.705	0.659
zrx	0.815	0.796	0.923
waves	0.974	0.95	0.977
omg	0.475	0.548	0.644
dgb	0.635	0.441	0.24
ren	0.549	0.834	0.554
lsk	0.964	0.883	0.696
xvg	0.841	0.956	0.981
knc	0.352	0.601	0.577
rep	0.802	0.966	0.948
snt	0.29	0.495	0.701
ant	0.847	0.979	0.781
fun	0.702	0.395	0.319
cvc	0.629	0.877	0.683
gno	0.717	0.882	0.844
elf	0.844	0.693	0.688
gas	0.983	0.856	0.467

In this test, we saw that all the residuals do not show signs of autocorrelation

since they did not reject the null hypothesis of no autocorrelation.
Therefore, this model may be accepted.

2- Normality

To consider the distribution of the residuals, we have applied a normality test using the Jarque-Bera test.

Based on all the results, it appears that the residuals are not normally distributed since this test rejects the null hypothesis which is assuming that the data is generated by normally-distributed process.

Table 4.6: Normality test using Jarque-Bera

Test statistic	Critical value	p-value	Df
1.562e+06	99.62	0.00	78

3- Stability

Moreover, we tried to determine the stability of VAR(3) system by examining the eigenvalues of the VAR(3) representation Parameters.

We found that our model is stable since all the eigenvalues are less than 1, in absolute value.

4- Correlation in the residuals

Furthermore, we checked the correlation between the residuals of our model.
In the figure below, we show that the cryptocurrencies with the highest market capitalization have higher correlation with each other, which indicates that these cryptocurrencies are not totally independent.

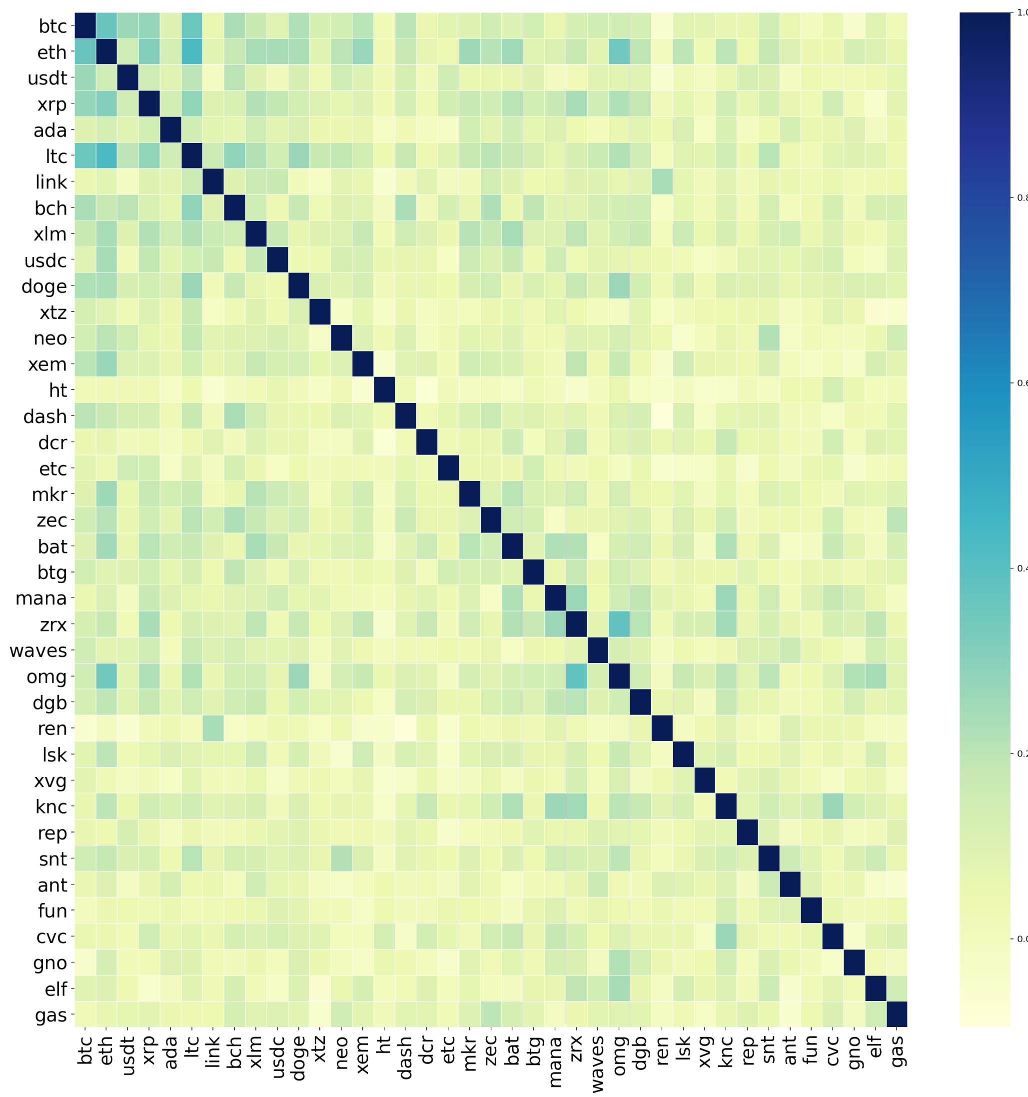

Figure 4.11: Correlation in the residuals

Therefore, this VAR model with lag of order 3, which have been used for illustration, satisfied all the conditions.

4.2 VAR with LASSO

Using VAR with large samples (39 cryptocurrencies) will lead to over-parameterization, as the VAR model estimates $pN^2 + p$ regression parameters. The number of parameters increases quadratically with the number of variables. Hence, even moderately sized systems can become highly over-parameterized relative to the number of data points.

In our case, the VAR model has a lag of order 3, and with the number of variables $N = 39$, we end up with 4335 regression parameters.

This heavy parameterization is the major drawback of the VAR and it limits its applicability because while estimating such a highly parameterized system, this may cause multicollinearity and provide a rapid running out of the available degrees of freedom, which may affect the efficiency of the estimation, and lead to large out-of-sample forecast errors.

Therefore, in the analysis of this high-dimensional data (39 cryptocurrencies), we exploit the least absolute shrinkage and selection operator (LASSO) method to reduce dimensionality and shrink the sample when estimating VAR parameters.

the order of our model chosen was three, which is the same as our previous model. We tried to decrease the lag order to see if we can reduce the number of parameters, but there was a clear presence of serial correlation. For that reason, we kept the same lag order which gives acceptable results.

After identifying the VAR model, we tried to estimate it by minimizing equation by equation the LASSO criterion to shrink some of the parameters to zero and that is by adding the penalty term which is multiplied by a tuning parameter. And to find the best tuning parameter, we used five-fold cross-validation (CV).

4.2.1 Coefficients

In the figure below, we show the coefficients in each equation of our model.

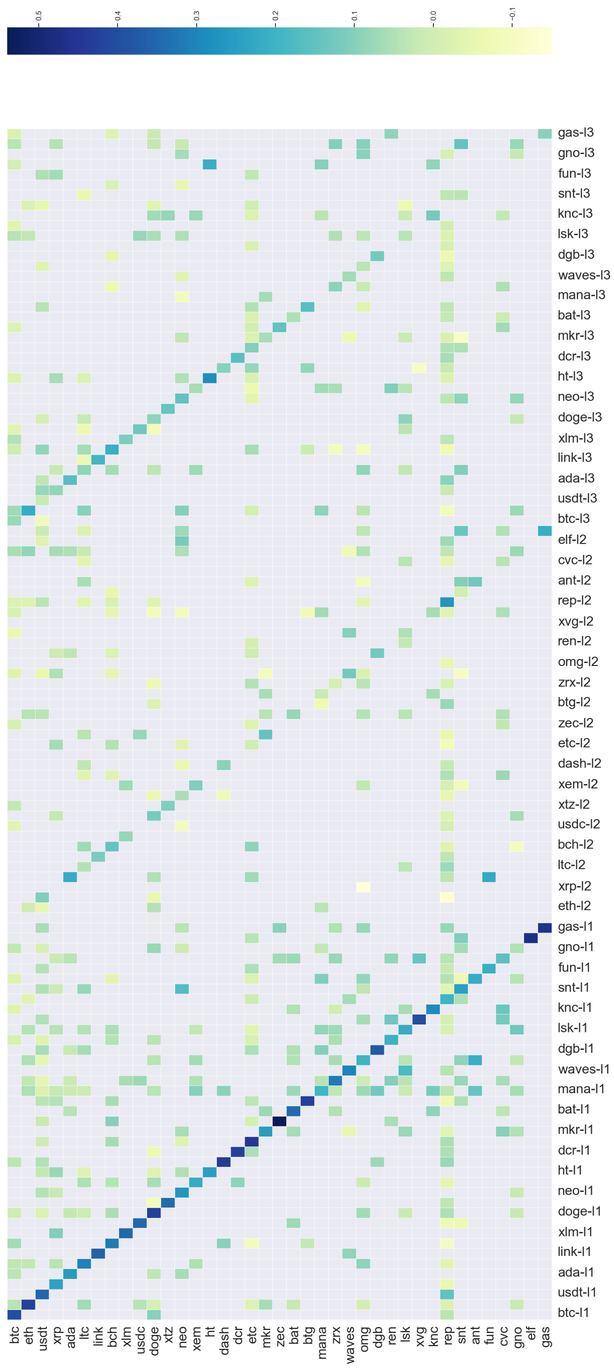

Figure 4.12: Coefficients after using LASSO

After using LASSO, a large number of coefficients have been shrinked to zero. This reduced model will help us to find more efficient results for our variance decomposition.

We see that cryptocurrencies are mostly influenced by their lagged values, and also by some of the lagged values of other cryptos.

4.2.2 Diagnostics

1- Autocorrelation

After estimating the model, we can perform some diagnostic tests on the residuals of the model.

we first started by checking the serial correlation using Ljung-Box test of autocorrelation in residuals, our goal is to find residuals with, as much as possible, no serial correlation.
the null hypothesis is having no autocorrelation. And the results of this test is shown in the table below.

Table 4.7: P_values for the serial correlation test of the var model with LASSO

	lag1	lag2	lag3
btc	0.268	0.218	0.385
eth	0.862	0.93	0.151
usdt	0.989	0.986	0.373
xrp	0.374	0.382	0.566
ada	0.793	0.291	0.029
ltc	0.849	0.955	0.625
link	0.632	0.504	0.066
bch	0.606	0.409	0.173
xlm	0.835	0.922	0.946
usdc	0.701	0.795	0.205
doge	0.677	0.666	0.152
xtz	0.598	0.467	0.109
neo	0.755	0.521	0.256
xem	0.912	0.925	0.748
ht	0.713	0.906	0.714
dash	0.929	0.846	0.756
dcr	0.659	0.723	0.067
etc	0.816	0.834	0.844
mkr	0.96	0.983	0.774
zec	0.897	0.967	0.19
bat	0.635	0.661	0.84
btg	0.86	0.957	0.584
mana	0.908	0.99	0.218
zrx	0.52	0.813	0.908
waves	0.924	0.994	0.992
omg	0.735	0.206	0.278
dgb	0.847	0.678	0.128
ren	0.653	0.64	0.013
lsk	0.548	0.835	0.908
xvg	0.959	0.998	0.83
knc	0.668	0.904	0.292
rep	0.979	0.963	0.779
snt	0.813	0.875	0.888
ant	0.606	0.671	0.85
fun	0.551	0.024	0.033
cvc	0.738	0.919	0.982
gno	0.946	0.996	0.818
elf	0.097	0.246	0.0
gas	0.664	0.353	0.004

The results indicate no rejection of the null hypothesis for mostly all of the cryp-

tocurrencies residuals, we saw that we have just two cryptocurrencies whose residuals do show signs of serial correlation (residuals of Aelf(elf), and residuals of gas).
Therefore, this model may be accepted.

2- Normality

After testing the autocorrelation, we applied a normality test using the Jarque-Bera test to check the residual distribution.

Table 4.8: Normality test using Jarque-Bera

Test statistic	Critical value	p-value	Df
2.785e+06	101.9	0.000	80

Based on all the results,the Jarque-Bera test supports the latter findings by rejecting the null hypothesis which is assuming that residuals are normally-distributed at 5% significance level.
therefore, the residuals are not normally distributed.

3- Stability

Moreover, we tried to examine the stability of our VAR system based on the eigenvalues where all the eigenvalues should be less than 1 in absolute value. And it appeared that our model is stable.

4- Correlation in the residuals

Furthermore, we checked the correlation between the residuals of our model.

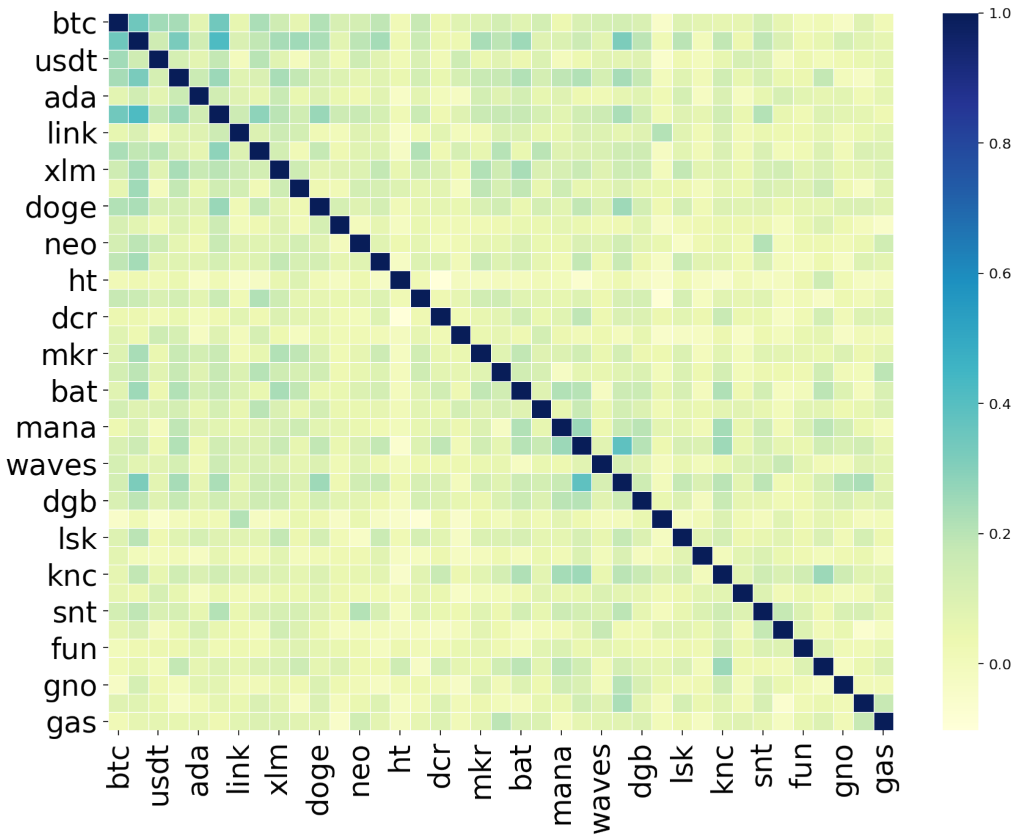

Figure 4.13: Correlation in the residuals

From this figure, it is clear that there are some correlation in the residuals.
The correlation tends to be higher among the large cryptocurrencies,based on their market capitalization as we can see that there are higher correlation between bitcoin, ethereum and Ripple than between the smaller ones such as gas, fun, gno.
This indicates that these cryptocurrencies are not totally independent. It could be that there are common factors that cryptocurrencies tend to load on them higher, when the market capitalization is high.

4.3 Variance Decomposition

We believe that using LASSO with VAR model is more efficient with our large sample. Therefore, the variance decomposition will be based on the residuals given by this model.

To make the component of the error term independent, we need to first standardize them to make them uncorrelated, then we need to rotate the resulting matrix so that we have independent components as much as possible.

The independent component analysis separates sources by maximizing their non-Gaussianity. Hence, data with Gaussian distribution may not be separated. For this reason, we made sure that we do not have normally distributed residuals before applying the ICA.

This standardization and the rotation are both performed by the FastICA algorithm in python, which first whitens the residuals then performs the rotation by minimizing the gaussianity of the projected residuals in order to recover the residuals which are statistically independent in a unique way.

After obtaining these independent residuals, we used them instead of the actual residuals in VMA representation.

To get all aspects of connectedness, we considered estimating network connectedness at the forecast horizon $H = 10$ and with the lag order $p = 3$.

The estimated forecast error variance of each cryptocurrency contributed by innovations to other cryptocurrency is shown by the below heatmap.

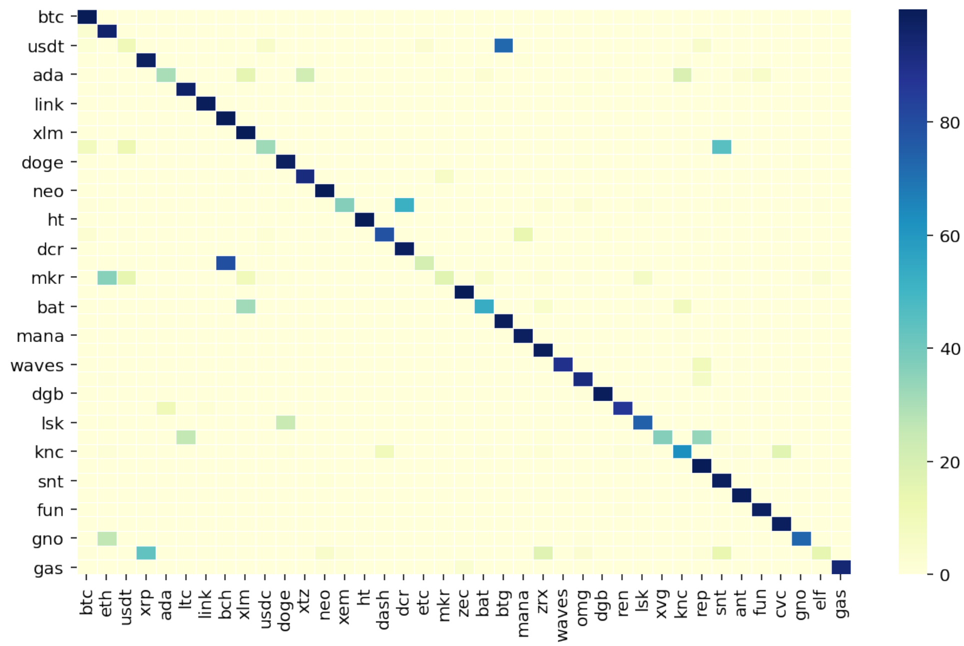

Figure 4.14: Heatmap that explains the NVT connectedness table for cryptocurrencies

This heatmap explains the NVTAjusted spillovers across our cryptocurrencies, i.e. how the shocks are transmitted over these various assets.

We discuss the diagonal elements which represent each cryptocurrency own connectedness, we see from this heatmap, that the NVT shocks of cryptocurrencies that come from themselves are the largest individual elements and most of them are above 70%.

The largest among them is Cardano(ADA)'s own connectedness with 99.99% , Chainlink(link)'s own connectedness with 99.98% , Bitcoin cash(bch) with 99.11%, Doge coin with 99,57% and Huobi Token(ht) with 99.98%.

We discuss the off-diagnonal elements which represent the pairwise directional connectedness.

We observe that there are some cryptocurrencies that are significant transmitters of this network connectedness and that they even have a larger contribution of spillovers to others.

We see that the innovations to bch are responsible for 27.906% of the error variance in forecasting ten days ahead of btg's NVT value.

Moreover, it contributes to 24.516% of the error variance in forecasting 10 days ahead of Ethereum(etc)'s NVT value.

Also, one of largest pairwise directional connectedness is from ltc to rep with 29.372%, while the pairwise directional connectedness from etc to bch is 0.07%,so the net pairwise connectedness from etc to bch is 29.3%.

The second largest pairwise directional connectedness is from Cardano(ada) to ant (24.001%). In return, the pairwise directional connectedness from ant to ada is (0.001%), therefore the spillovers from Cardano to ant are larger than from ant to cardano.

Additionaly, the innovations to snt are responsible for 19.197% of the error variance in forecasting ten days ahead of neo's NVT value. And it contributes to 25.988% of the error variance in forecasting 10 days ahead of (elf)'s NVT value.
However, it only contributes to 1.70% of the error variance in forecasting 10 days ahead of (ltc)'s NVT value.

Table 4.9: The from-connectedness, to-connectedness and net-connectedness of the cryptocurrencies

	btc	**eth**	**usdt**	**xrp**	**ada**	**ltc**	**link**	**bch**	**xlm**	**usdc**	**doge**	**xtz**	**neo**
From	2.965	12.822	11.491	20.591	0.007	33.590	0.012	0.888	0.143	1.470	0.430	0.550	20.673
To	2.390	8.460	6.721	15.457	25.694	29.957	0.000	55.276	2.543	3.795	45.761	0.062	23.942
Net	0.575	4.362	4.770	5.134	-25.687	3.633	0.012	-54.388	-2.400	-2.325	-45.331	0.488	-3.269
	xem	**ht**	**dash**	**dcr**	**etc**	**mkr**	**zec**	**bat**	**btg**	**mana**	**zrx**	**waves**	**omg**
From	1.776	0.007	0.027	0.129	24.525	0.118	0.499	55.560	41.944	9.873	21.438	0.048	13.184
To	3.221	2.308	2.687	1.478	18.600	6.058	5.791	0.670	0.044	34.970	16.090	7.652	65.288
Net	-1.445	-2.301	-2.660	-1.349	5.925	-5.940	-5.292	54.890	41.900	-25.097	5.348	-7.604	-52.104
	dgb	**ren**	**lsk**	**xvg**	**knc**	**rep**	**snt**	**ant**	**fun**	**cvc**	**gno**	**elf**	**gas**
From	5.096	25.870	2.695	10.098	3.364	30.432	0.003	24.281	53.923	5.719	1.274	48.268	5.422
To	0.277	0.776	2.590	0.207	0.472	3.259	50.039	1.968	0.074	24.402	3.558	0.000	0.000
Net	4.819	25.094	0.105	9.891	2.892	27.173	-50.036	22.313	53.849	-18.683	-2.284	48.268	5.422

The above table contains the off-diagonal column and row sums of the table, which are contributions to others and contribution from others, respectively. Where the row sum is 100%, so the NVT connectedness from others is equal to 1 minus the diagonal eelement.

We have also defined the net connectedness in this table, which is the difference between "to" and "from".

The cryptocurrencies with the largest net-connectedness are fun with 53,823%, bat with 52.27 %, elf with 48,268% which means that these are the highest cryptocurrencies that receive from others way more than they contribute to others.

Therefore, investors should invest less in them,since they are influenced by the spillovers the most.
We can also identify from this table the cryptocurrencies with the smallest risk of being influenced by shocks to other cryptocurrencies. We list the ones with the least risk: Cardano(ada) where the contribution from others to it equal to 0.07% ,for ht with also 0.07%, dash with 0.027%, snt with 0.003% and link with 0.012%
What characterize Chainlink (link) from others, is that it is one of the smallest recipient of network connectedness (0.012%) and the smallest transmitter as it does not contribute to any other cryptocurrency shocks.

The cryptocurrencies that have the largest contributions to others are the following, omg with 72,479%, bch with 55,3%, snt with 50,04%, and doge with 45,87%.
Therfore, Market participants should take this into account when investing in cryptocurrencies.

We also observe that Bitcoin, which the highest cryptocurrency by market capitalization do not generate widespread connectedness since it has a small contribution in transmitting shocks to other cryptocurrencies (2.43%), and it also receive small NVT spillovers from other cryptocurrencies (with 2.96%).

The key substantive summary result to emerge from this table that, distilling all of the various cross-cryptocurrencies spillovers into a single Spillover Index for our full 2018-2021 data sample, we find that almost 13% of forecast error variance comes from spillovers.
Hence spillovers could be interesting to understand the interaction between these various cryptocurrencies.

4.4 Network Connectedness

This population connectedness is effective when analyzing a small sample. But when it comes to applying it to a large sample of data, its applicability will be reduced because of its heavy parameterization since any two firms are connected to each other in the network by edges in both directions.
In our case, we have 1482 different pairwise directional connectedness measures ($p^2 - p$).
Therefore, to display the results of high-dimensional network intuitively, between each two cryptocurrencies we kept only one direction where the shocks to variable A that affect the forecast error variance(FEV) of variable B have a bigger contribution than the latter's shocks that affects the FEV of variable A.

We characterize the networks graphically using several devices. These devices include node's naming convention, node's size, node's color, and edge's direc-

tion.
Node's naming convention is short for each cryptocurrency, node's size indicates either the from-connectedness or to-connectedness.
And we tried to specify different characteristics of cryptocurrencies based on the node's color: for each network it is either indicates the size of their relative market capitalization, or the consensus mechanism that have been used, or based on each cryptocurrency's category.

Note that the edges whose NVT pairwise directional connectedness or spillover from one cryptocurrency to another less than 0.05 are not shown in the plots. In addition, the size of each edge is based on the pairwise directional connectedness value.

4.4.1 Based on the market capitalization

To specify the cryptocurrencies based on their market capitalization, we divided the cryptocurrencies into several ranges according to the size of their market capitalization.
For instance, Bitcoin, the only cryptocurrency whose market value surpassed 800 billion USD, is marked red. Ethereum, whose market cap surpassed 100 billion USD, is marked indianred.
The colors for the remaining currencies also indicate the relative size of their market values, including lightcoral (indicating a currency's market value between 10 and 100 billion USD), darksalmon (between 2 and 10 billion USD), salmon (between 1 and 2 billion USD), lightsalmon (between 500 million and 1 billion USD), and peachpuff (below 500 million USD)

In the figure below, we show the connectedness network linking our 39 cryptocurrencies, based on the their market capitalization and their contribution to others.

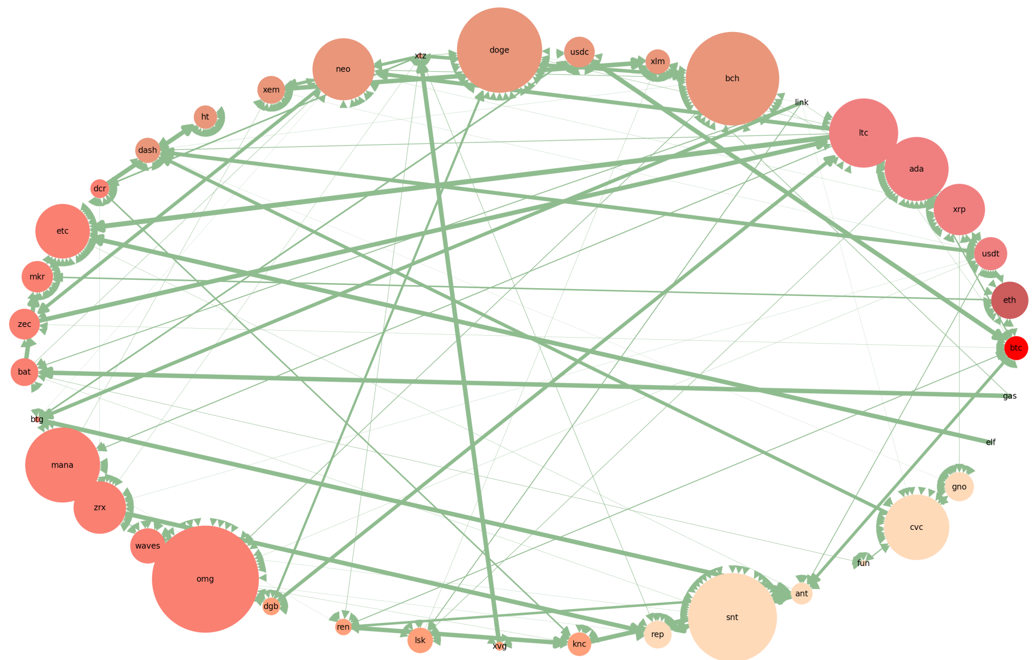

Figure 4.15: Connectedness network linking 39 cryptocurrencies based on the their market capitalization and their contribution to others

This network linking our 39 cryptocurrencies indicates that the NVT connectedness among cryptocurrencies does not necessarily depend on their size: we have some of the mega-cap cryptocurrencies that are high transmitters to others such as Cardano (ada), Litecoin, Bitcoin cash,Doge coin and neo .

We see that there are also some cryptocurrencies whose market capitalization between 1 and 2 billion USD are high transmitters to shocks to others such as Ethereum(etc),mana, 0x(zrx) and especially OMG network which have an immense impact on other cryptocurrencies's shocks.

In addition, other cryptocurrencies with low market capitalization (below 500 million USD) such as Status(snt) and Civic(cvc), are more likely to propagate NVTAjusted shocks to others.

What is interesting is that bitcoin is not the dominant player of this NVT connectedness in the cryptocurrency market, since it is not the highest transmitter to others, on the contrary, it is one of the lowest ones.

Moreover, the shocks to cryptos with low market cap, that affect the forecast

error variance(FEV) of cryptos with high market cap, have a bigger contribution than the latter's on the FEV of low market cap cryptocurrencies.
For instance, DigiByte(dgb) is a big transmitter to shocks to ltc. The same with elf to etc and with gas to bat.

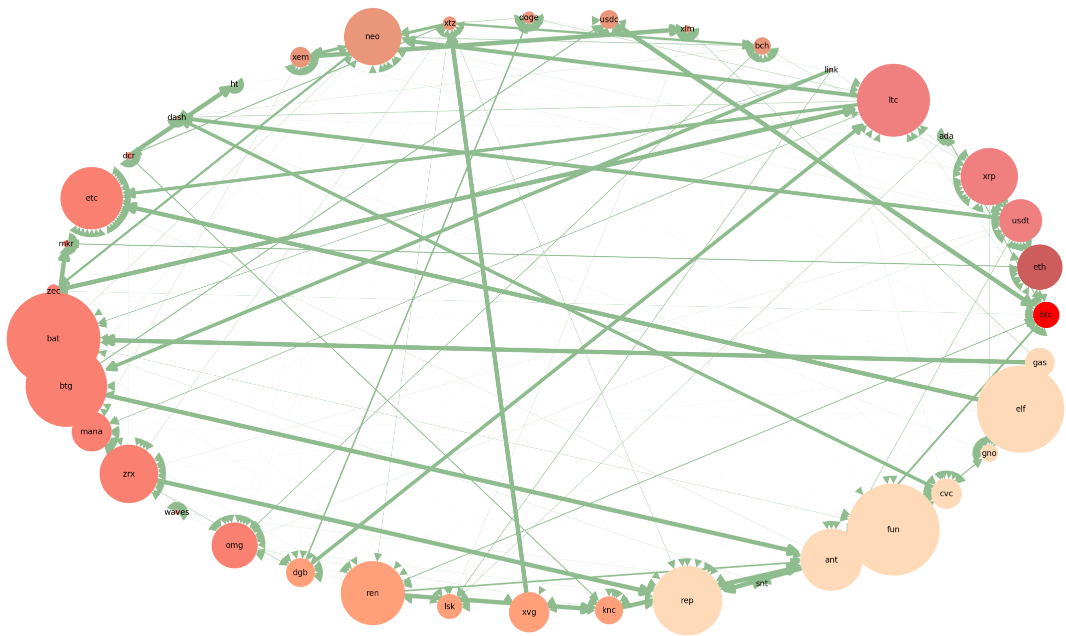

Figure 4.16: Connectedness network linking 39 cryptocurrencies based on the their market capitalization and their contribution from others.

From this network, we see that the cryptocurrencies that have low market capitalization (those with market cap below 500 million USD , and between 1 and 2 billion USD) receive the most shocks from other cryptos. naming few: Basic Attention Token(bat), Bitcoin Gold(btg),0x(zrx),fun,Aelf(elf),Aragon(ant), and Augur(rep).
Moreover,we have identified that some cryptocurrencies with the highest market cap such as xrp and especially Litecoin receive a big amount of shocks from other assets.

The results from these two networks indicate that the chosen cryptocurrencies are interconnected and the intensity of connectedness between pairwise cryptocurrencies is not fully determined by market capitalization since both cryptocurrencies with the highest and lowest market capitalization take an important role in NVT connectedness of the whole market.

4.4.2 Based on the consensus mechanism

To further examine relative influence of cryptocurrencies in the network, we also employed the consensus mechanism to characterize each cryptocurrency. These consensus mechanisms are used in the blockchain systems to ensure that all the transactions occurring on the network are genuine and all participants agree on a consensus on the status of the ledger.
These algorithms are important since these Public Blockchains operate as decentralized, self-regulating systems without any single authority.

Therefore, this set of rules decides on the contributions by the various participants who work on verification and authentication of transactions occurring on the Blockchain, and on the block mining activities.

There are different types of consensus mechanism algorithms that work on different principles. the most popular are Proof of Work (PoW) and Proof of Stake (PoS).
POW refers to an agreement algorithm that proves that it has completed the task of adding a new Blockchain. Many cryptocurrencies rely on it such as bitcoin, dash, doge... However, this consensus mechanism absorbs a huge amount of energy to verify transactions and mint new coins.

Therefore, many altcoins are using PoS. It is more efficient as it refers to an agreement algorithm that gives decision-making authority in proportion to the percentage of shares held in cryptocurrency.
The market-leading coins using PoS are Cardano (ADA), Polkadot and Stella.
There is also Delegated Proof of Stake (DPoS) which is popular evolution of the PoS concept, whereby users of the network vote and elect delegates to validate the next block. In our data we only have Lisk(lsk) that relies on that.
There are also many other consensus mechanisms that aim to have a more efficient system.

In our network, we have tried to distinguish between cryptocurrencies that use PoW and those that use PoS, in order to reveal tendency in the data. Each color specify one type of consensus mechanism: PoW in blue, PoS in lightcoral, dPos in indianred , and the others are in yellow.

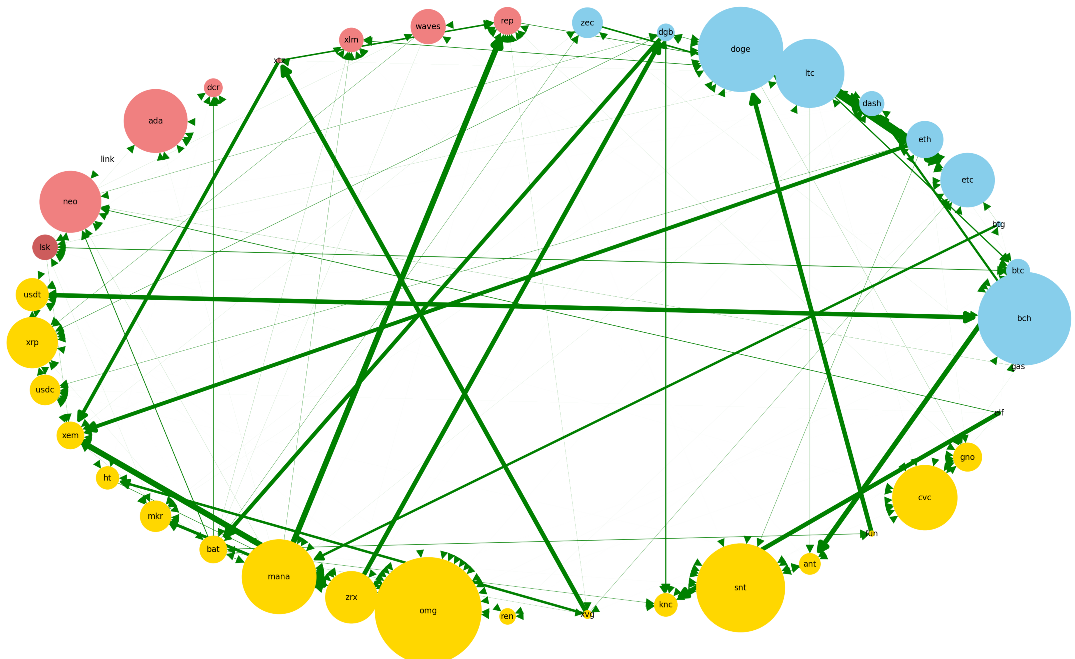

Figure 4.17: Connectedness network linking 39 cryptocurrencies based on the their consensus mechanism and their contribution in transmitting shocks to others.

From this network, we see that only three of the cryptocurrencies that rely on Proof-of-work have a large contribution in transmitting shocks to other cryptocurrencies. such as Bch, doge and ltc.
And only Cardano(ada) and neo , which belong to the group of cryptocurrencies that use Proof-of-Stake, have a high contribution in transmitting shocks to others.

We have also some cryptocurrencies that use another consensus mechanism rather than PoW and PoS and have a high contribution in transmitting shocks to others such as mana, Status(snt) and omg which is currently secured by proof-of-authority(POA) consensus mechanism.

We observe large contributions in transmitting shocks to others within cryptos that use Proof-of-work and also within cryptos that use consensus mechanism other than PoW and PoS.
And mostly the cryptocurrencies that rely on consensus mechanism other than PoW and PoS are the ones that contribute the most to cryptos that use PoW or PoS.

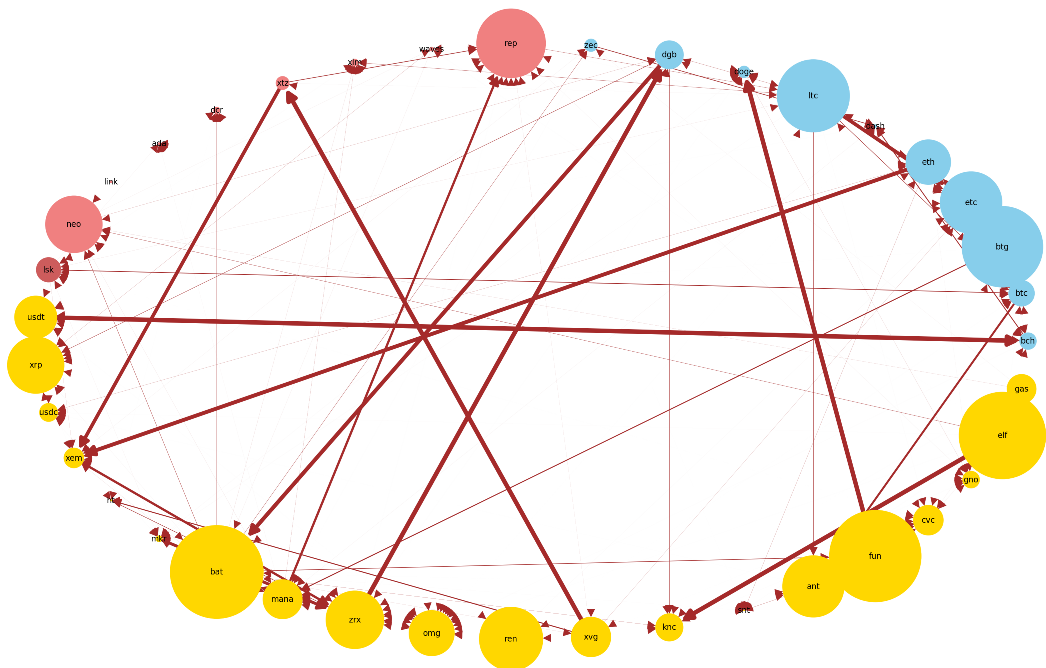

Figure 4.18: Connectedness network linking 39 cryptocurrencies based on the their consensus mechanism and their contribution in receiving from others

We see that mostly the only cryptocurrencies that receive small NVT spillovers from other cryptocurrencies are the ones that rely on Proof-of-stake. There are only rep and neo receive higher spillovers from other assets.
We observe that the highest pairwise directional connectedness values are coming from the cryptocurrencies that use consensus mechanism other than PoW and PoS, towards the other assets. Such as from mana to rep, or from Tether(usdt) to Bitcoin Cash (bch).
Mostly, the highest transmitters and highest receivers are the cryptocurrencies that use consensus mechanism other than PoW and PoS.

Our results prove that cryptocurrencies that rely on Proof-of-stake or dPoS (other than rep and neo), are the smallest receivers of NVT spillovers from other cryptocurrencies, and since we observe small contributions in transmitting shocks to others within cryptos that use Proof-of-stake, it means that these cryptocurrencies are less interconnected and that will be useful to obtain diversified risks, therefore, market participants may be interested in investing in this group of altcoins.

Moreover, mining cryptos that use PoS is more efficient since it does not require a highly complex computation, compared to PoW cryptos. Hence this will lead to low electricity costs and small material purchase costs to verify transactions.

4.4.3 Based on their Category

Each cryptocurrency is used for a different purpose, it could for security, payment, smart contracts...Therefore, we grouped different cryptocurrencies by their utility.

The categories that have been chosen are smart contracts, payment, medium of exchange,DeFi, enterprise solution, and privacy, where DeFi cryptocurrencies are essentially providing financial services like savings, loans, trading, insurance and more to practically anyone with an internet-enabled smartphone. And a smart contract crypto is a self-executing contract with the terms of the agreement between buyer and seller being directly written into lines of code.

Each color specify one category: skyblue for smart contracts, indianred for deFi, aqua for privacy, greenyellow for medium of exchange,yellowgreen for payment, and orchid for enterprise solution.

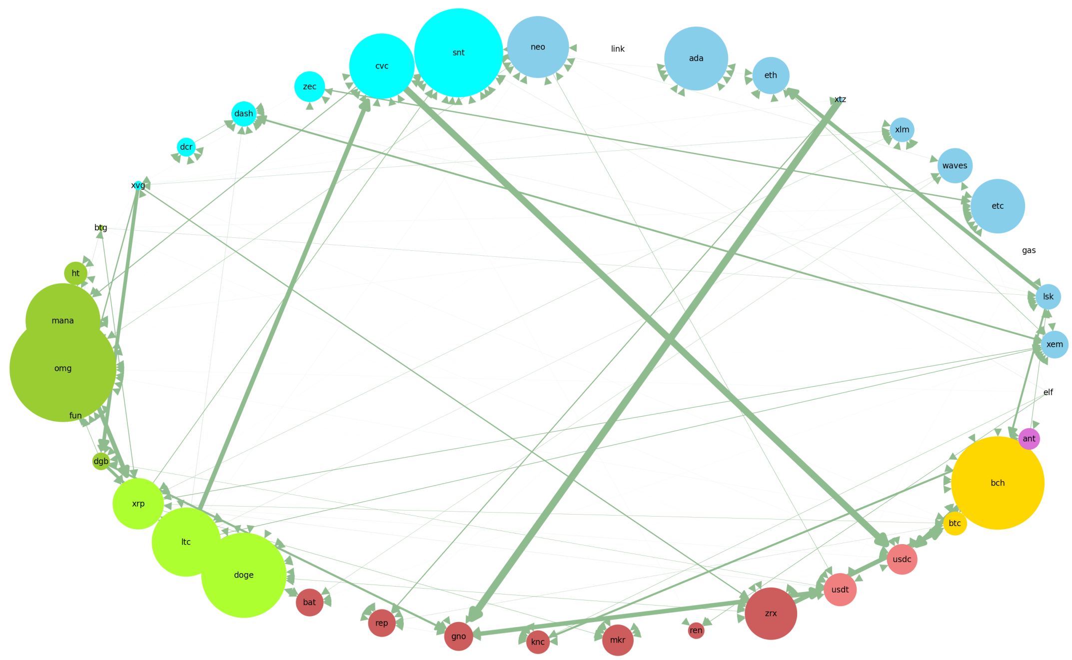

Figure 4.19: Connectedness network linking 39 cryptocurrencies based on the their categories and their contribution to others

This network indicates that most of the cryptocurrencies that are used for either payment or medium of exchange such as Doge, Litecoin, omg, and Bitcoin cash, have the largest contribution in transmitting shocks to other cryptos.
These results also indicate that the cryptocurrencies that are used for enterprise solution such as ant, and deFi cryptocurrencies (such as bat, rep) have the lowest contributions in transmitting shocks to others.
And for the altcoins used for privacy, we only have snt and cvc that have high contribution to others.

In addition, some of the cryptocurrencies that are used for smart contracts have large contributions of NVT spillovers to others, such as Cardano(ada), neo and etc.

We see a high interconnection within cryptos used for payment and medium of exchange.
We also observe that cryptocurrencies in deFi category have a high pairwise directional connectedness value transmitted to them from other categories such as privacy (cvc, snt), smart contracts(xtz) and medium of exchange(xrp).

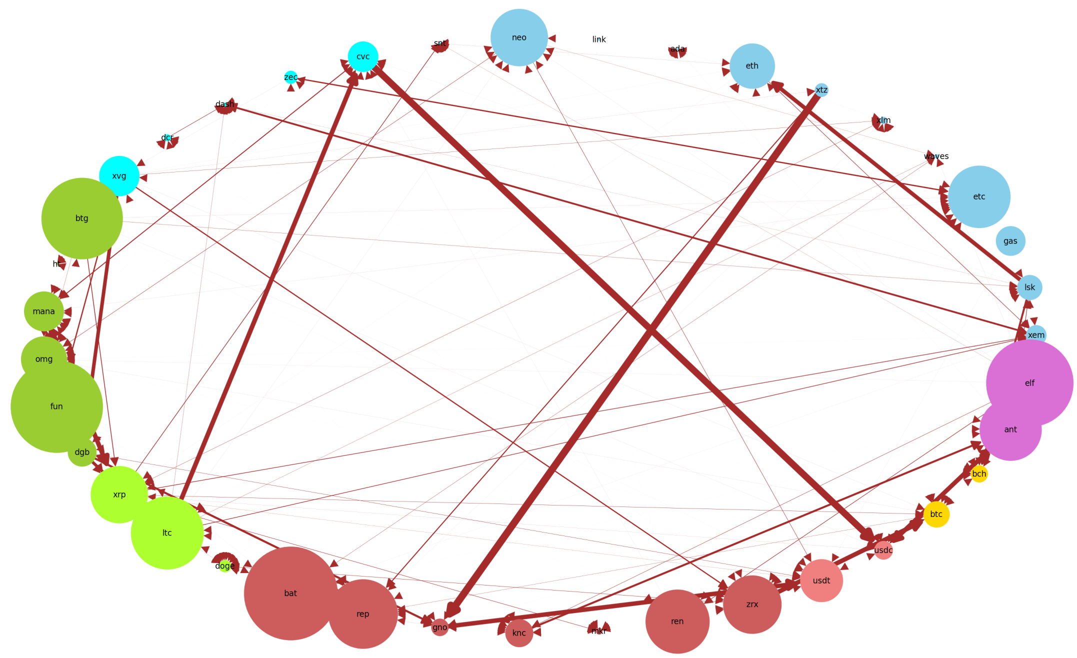

Figure 4.20: Connectedness network linking 39 cryptocurrencies based on the their categories and their contribution from others

We see that mostly the cryptocurrencies used for payment, deFi, and enterprise solution receive higher shocks from other assets.
Moreover, some of the cryptocurrencies used for smart contracts receive high contributions from others such as etc, eth and neo.
However, we see that cryptos used for privacy(xvg, dcr, dash, zec, cvc, snt) receive small NVT spillovers from other cryptocurrencies, and the spillovers within this category are so small.

Therefore, this result indicates that the cryptocurrencies that are used for privacy are the least interconnected, and receive small spillovers from other cryptos. This will attract market participant attention as it will lead them to invest more in this category of altcoins.

5 Conclusion

The main objective of this capstone is to assess the network connectedness or spillovers among various cryptocurrencies at a system-wide level, in order to provide new information to market participants who are interested in investment or hedging strategies in cryptocurrencies.
This would help them choose an appropriate cryptocurrency to adjust their asset portfolio based on their risk preference.
In addition, this could be useful for miners as it provides them with information that may help them identify and mine the less interconnected cryptocurrencies to obtain diversified risks.

Therefore, to investigate the relationship between Cryptocurrencies (39 cryptocurrencies from the world's top 400 by market capitalization on February 2021), we have provided static analyses of NVT connectedness among these cryptocurrencies from November 2018 to February 2021, using the spillover index and its variants.
This was essentially based on the variance decompositions process in the vector autoregressions model, where we have used LASSO to shrink the parameters in our high-dimensional data and build the VAR model. To get afterwards the NVT connectedness network
In addition, we have tested the robustness of results in terms of the choice of VAR lag order.
Our spillover measures have provided us with important and useful information:
One of our interesting findings is that the NVT connectedness or spillover effect is not necessarily linked to market capitalization. Since we found that cryptocurrencies with high market capitalizations (e.g. Litecoin and Dogecoin, Bitcoin cash) propagate large NVT shocks, and even the small-cap cryptocurrencies are also important emitters of NVT shocks (e.g., cnt, cvc, omg, mana). More importantly, the largest emitter of NVT shocks in the cryptocurrency market is omg, which catches less attention of the public.

Another interesting finding is that bitcoin is not the dominant cryptocurrency when it comes to NVT shocks, even though it plays an important role in this cryptocurrency market, however, it has a small contribution to the spillovers to the other altcoins. (as it contributes small NVT shocks to the other altcoins in our data). Therefore, the NVT values of altcoins are not driven by Bitcoin.

Moreover, our work provided us with new information about cryptocurrencies that rely on Proof-of-stake and delegated Proof-of-stake as consensus mechanism, which are the smallest receivers of NVT spillovers from other cryptocurrencies, these cryptos are also the least interconnected with each other. Hence, market participants may be interested in investing in this group of altcoins to obtain diversified risks.

Moreover, mining cryptos that use PoS is more efficient since it does not require high electricity costs and high material purchase costs to verify transactions.

We have also found that the cryptocurrencies that are used for privacy are the least interconnected, and receive small spillovers from other cryptos.
This may also attract market participants attention.

Our investigation on NVT connectedness among cryptocurrencies and examining which cryptocurrency generates strong NVT shocks to others complement the literature on cryptocurrency and provide new information for market participants.

As for future work, there are several interesting directions for an extension. It would be interesting to try to move from a full-sample static analysis to a rolling-sample dynamic analysis, in order to examine the cycles if they exist, and analyze them with the relevant events that may cause them.

References

Cheah, Eng-Tuck, and John Fry. 2015. Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. Economics Letters 130: 32–36.

Chen, Cathy Y. H., Romeo Després, Li Guo, and Thomas Renault. 2018. What Makes Cryptocurrencies Special? Investor Sentiment and Price Predictability in the Absence of Fundamental Value. Discussion Paper Sfb 649. Unpublished work.

Chen, Cathy YH, CM Hafner (2019). Sentiment-induced bubbles in the cryptocurrency market, Journal of Risk and Financial Management.

Cheung, Adrian, Eduardo Roca, and Jen-Je Su. 2015. Crypto-currency bubbles: An application of the Phillips-Shi-Yu (2013) methodology on Mt.Gox bitcoin prices. Applied Economics 47: 2348–58.

Corbet, Shaen, Brian Lucey, and Larisa Yarovaya. 2018. Datestamping the bitcoin and ethereum bubbles. Finance Research Letters 26: 81–88.

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

Diebold, F. X., Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119, 158–171.

Diebold, F. X., Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers.*International Journal of Forecasting*, 28, 57–66.

Diebold, F.X., Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics*, Volume 182, 119-134.

Elendner, Trimborn, Ong and Lee (2016), The Cross-Section of Crypto- Currencies as Financial Assets: An Overview, SFB discussion paper, Humboldt University Berlin.

Fry, J., Cheah, E. T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, 47, 343–352.

Hafner, C. (2020). "Testing for Bubbles in Cryptocurrencies with Time-Varying Volatility," *Journal of Financial Econometrics, Society for Financial Econometrics*, vol. 18(2), pages 233-249.

Kjaerland, Frode, Aras Khazal, Erlend A. Krogstad, Frans B. G. Nordstroem, and Are Oust. 2018. An analysis of bitcoin's price dynamics. Journal of Risk and Financial Management 11: 63.

Koop, G., Pesaran, M. H., Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74, 119–147.

Lütkepohl, H. (2005), New introduction to multiple time series analysis, Springer Verlag.

Nasekin, Sergey, and Cathy Yi-Hsuan Chen. 2018. Deep Learning-Based Cryptocurrency Sentiment Construction. Available at SSRN 3310784. J. Risk Financial Manag. 2019, 12, 53 12 of 12

Phillips, Peter C. B., Shuping Shi, and Jun Yu. 2015. Testing for multiple bubbles: Historical episodes of exuberance and collapse in the s&p 500. International Economic Review 56: 1043–78.

Phillips, Peter C. B., Yangru Wu, and Jun Yu. 2011. Explosive behavior in the 1990s nasdaq: When did exuberance escalate asset values? International Economic Review 52: 201–26.

Pesaran, H. H., Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58, 17–29.

Sims, C. A. (1980). Macroeconomics and reality. Econometrica, 48, 1–48.

Yi, Shuyue Xu, Zishuang Wang, GangJin, 2018. "Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?," *International Review of Financial Analysis, Elsevier*, vol. 60(C), pages 98-114.

Appendices

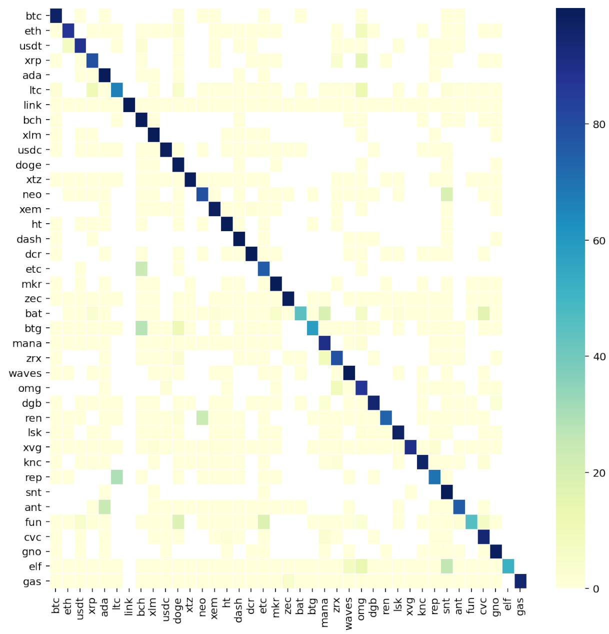

Figure .1: Variance decomposition matrix after reducing the number of edges