ANALYSIS OF CRYPTOCURRENCY CONNECTEDNESS BASED ON NETWORK TO TRANSACTION VOLUME RATIOS

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Analysis of cryptocurrency connectedness based on network to transaction volume ratios

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Abstract

Network to Transaction (NVT) ratio is a measure that describes the relationship between transaction volume and market capitalization, and that may serve as an indicator for the valuation of a cryptocurrency. We build a connectedness network connecting 39 cryptocurrencies based on mutual contributions to the variances of forecast errors for NVT ratios. We find that NVT connectedness is not 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). The largest transmitter of NVT shocks is OMG Network, which receives little public attention. Cryptocurrencies relying on proof of stake as a consensus mechanism are the smallest receivers of NVT spillovers from other cryptocurrencies. These assets are also the least interconnected, which makes them attractive from a risk diversification point of view. This complements the energy efficiency of PoS compared with proof of work.

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

JEL classification: **C14, C43, Z11**

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1 Introduction

Cryptocurrencies, unlike traditional currencies and assets, are decentralized digital currencies or assets that are not regulated by any central institution or government. The aim is to ensure anonymity, low cost and fast speed of peer-to-peer transactions based on crypto protocols, although this may be realized only to some extent in most cases, see e.g. Härdle et al. (2020). Moreover, high volatility and limited liquidity of smaller cryptocurrencies is an issue that needs to be taken into account in investment strategies, as emphasized by Trimborn et al. (2020) and Petukhina et al. (2020).

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, with more than 4,000 different cryptocurrencies in existence as of January 2022[1]. The top 20 cryptocurrencies make up nearly 90 per cent of the total market. One reason for the large number of existing cryptocurrencies is that they are relatively costless to create, while a large portion of them has little to no trading volume, see e.g. Härdle et al. (2020). As a result, many investors are concerned with the valuation of digital assets with an incentive to detect whether it reflects a fundamental value, or whether they are just forming speculative bubbles, see e.g. Bouri et al. (2017) and Cheah and Fry (2015).

In 2017, coinmetrics.io introduced the network value-to-transaction (NVT) ratio as a method of valuing crypto assets[2]. It is defined as the ratio of market capitalization and the on-chain transaction volume and can be viewed as the analogue of a 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). The NVT metric quantifies essentially the market valuation of the network against its usefulness as a payment network, where usefulness is approximated by the transaction volume. Therefore, it helps investors in spotting bubbles and investment opportunities. High NVT ratios hint at possible overvaluations, low ratios at undervaluations. In this study, we will be using an

[1] see e.g. coinmarketcap.com

[2] see https://coinmetrics.io/an-introduction-to-mtv/

adjusted measure of the NVT metric, proposed by coinmetrics in 2018[3], 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.

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. Investigating network connectedness contributes to understanding the information transmission mechanism in the cryptocurrency market and provides useful information for market participants such as investors to adjust their portfolio based on their risk preferences. Furthermore, this is informative for miners, as the mining process requires significant energy consumption and large material purchase costs. From a risk management perspective there is an incentive to mine the less interconnected cryptocurrencies, because mining rewards are typically payed in the own cryptocurrency, for example currently 6.25 BTC for mining one block of bitcoin transactions. Thus, the incentive is 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 use the framework of vector autoregressive models, see e.g. Sims (2002). Since we are analyzing high-dimensional data, we exploit the least absolute shrinkage and selection operator (LASSO) method, which imposes sparsity on the estimated coefficients and increases the prediction accuracy and interpretability of the statistical model. We then use the concept of forecast error variance decompositions to build a directional network of connectedness, reflecting the proportions of transmitted or received variances that are attributed to other cryptos. Using the spillover index approach and its variants (Diebold and Yilmaz, 2009, 2012, 2014), we measure both total and directional network connectedness across the cryptocurrencies. This provides information, for example, about directional causalities, in a predictability sense, of NVT ratios.

In order to overcome the limitations of the forecast variance decomposition, Diebold

[3]see https://coinmetrics.io/introducing-adjusted-estimates/

and Yilmaz (2012) have extended 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, and the sums of forecast error variance contributions are not necessarily unity, requiring additional standardizations.

The literature on cryptocurrencies has seen a surge recently. A good overview is given by Elender et al (2016). For example, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) have used the spillover index 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 suggest 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. The results of Lehner et al. (2021) suggest that the largest cryptocurrencies are still too volatile to justify their use in funding science or higher education. They call for more advanced valuation metrics to attract more institutional investors to this ecosphere.

Some papers 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. Furthermore, attempts have been made to link potential bubbles to investor sentiments, available for example via social networks. For crypoassets this 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. Using a different approach, Fry and Cheah (2016) have developed a model for financial bubbles and crashes and that was based on statistical physics and mathematical finance.

Only few papers pay attention to the relations between different cryptocurrencies. Shuyue Yia, Zishuang Xua, and Gang-Jin Wang (2018) applied the spillover index and its variants to the volatility connectedness in the cryptocurrency market. They have examined the static and dynamic volatility connectedness across eight different cryptocurrencies. For variance decompositions, they rely on the generalized variance decompostition framework of Koop et al. (1996) and Pesaran and Shin (1998). 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.

In this paper, we investigate the connectedness among 39 cryptocurrencies based on the NVT ratio. We do not distinguish between the different types of cryptocurrencies, assets and tokens, as they are numerous and the borders are fluid, and for simplicity call them cryptocurrencies or cryptos. For the variance decomposition, we use independent componenet analysis (ICA), which will be more effective than the approach of Diebold and Yilmaz (2012) 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 previous methods 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. The next section introduces our methodology. We then present our data and the empirical results of the application, and Section 4 summarizes the results and concludes.

2 Methodology

2.1 The model and estimation

Suppose we have N cryptoassets. We model here the NVT $y_{it}, i = 1, \ldots, N$, of crypto i at time t, via a vector autoregressive model (VAR) of the form

$$y_t = \mu + \sum_{j=1}^{K} A_j(y_{t-j} - \mu) + \varepsilon_t \tag{2.1}$$

where ε_t is a stochastic error term and A_j are $N \times N$ parameter matrices. The error terms satisfy $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Omega$, where Ω is an $N \times N$ positive definite variance-cobvariance matrix. Furthermore, $E(\varepsilon_t \varepsilon_{t-k}') = 0$, for any non-zero k. There is no serial correlation in the error terms.

We assume stationarity of the time series y_t, so that the usual stationarity conditions of the parameter matrices A_i apply. To determine the true lag order K for the model, Lutkepohl (1991) pointed out that selecting a higher order lag length than the true lag length 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.

For large N, there would be too many parameters to estimate for reasonable sample sizes. To tackle this issue we will use LASSO for variable selection. The Lasso imposes an L_1-penalty to the least squares loss function when estimating the parameters, to shrink some of them to zero, hence eliminating the corresponding variable. The choice of the penalty parameter is done by five-fold cross-validation. For instance, if information criteria suggest to choose a lag order of $K = 3$. We then estimate the model by minimizing equation by equation the following LASSO criterion

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

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

2.2 Forecast error 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.

It is important to have an orthogonal system, as it simplifies the calculation of the variance decomposition and ensures that the variance of a weighted sum is equal to a weighted sum of variances. However, the error terms ε_t of the VAR model are typically non-orthogonal. For that reason, we have to identify uncorrelated structural shocks from the residuals of the estimated VAR model. The original Cholesky-factor identification popularized by Sims is often used, but this method is sensitive to the ordering of the variables in the system.

An alternative of finding the underlying structural shocks is based on the independent component analysis (ICA) method which aims to find linear combinations of the error term ε_t that are independent, or at least as independent as possible. It is well known that independent components are identified under non-Gaussian distributions. To find the transformed error term u_t, we need to find the linear combination v of the error term ε_t,

$$u_t = v' \varepsilon_t$$

such that $\mathrm{Var}(u_t) = I_N$, where I_N is the identity matrix, and u_{it} is independent from u_{jt}, $i \neq j$.

A pre-processing is necessary before doing ICA to center and whiten the residuals. As the residuals of the estimated VAR model are already centered at zero by construction, we only need to orthogonalize them. The standardization of shocks u_t is defined as

$$\tilde{u_t} = \Omega^{-\frac{1}{2}}\varepsilon_t$$

where $\Omega^{-1/2}$ is the inverse of the symmetric square root of Ω, based on the spectral decomposition of Ω. 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. However, they are only independent under Gaussianity, which is excluded by our assumptions.

After 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. Therefore,

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

The rotation is performed by maximizing the distance from Gaussianity of the projected data in order to recover the original independent components. In particular, we use the so-called FastICA algorithm which identifies independent shocks in a unique way. FastICA is an efficient and popular algorithm introduced by Aapo Hyvärinen. As most ICA algorithms, FastICA seeks an orthogonal rotation of the pre-whitened data via a fixed-point iteration scheme that maximizes a measure of non-Gaussianity of the rotated components. We could have used alternatively the testing approach of Hafner et al. (2022), but as they show the differences to FastICA are typically small.

To obtain the forecast error variance decompositions, we use the VMA(∞) representation of the VAR(K) model. So, for example, if we consider the lag order of 2, then starting from the reduced form VAR(2) model in (2.1), 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 $\Phi_0 = I_N$, $\Phi_1 = A_1$, $\Phi_2 = \Phi_1 A_1 + A_2, \ldots, \Phi_j = \Phi_{j-1}A_1 + \Phi_{j-2}A_2, \ldots$, see e.g. Lütkepohl (2005). Based on the ICA, we can rewrite the model as

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

where $\Theta_j := \Phi_j \Omega^{1/2} R'$ and $u_t \sim (0, I_N)$. All aspects of connectedness are contained in this representation: the contemporaneous aspects are explained by Θ_0 and the dynamic ones are summarized by the other coefficients (Θ_1, Θ_2,..).

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. A large proportion $\omega_{ij,h}$ would then indicate that crypto i's forecast uncertainty, at a given time horizon, is to a large part explained by another crypto j, and can be interpreted as a spillover effect from crypto j to crypto i.

2.3 Network Connectedness

The analysis can be refined following Diebold and Yilmaz (2014) by viewing variance decompositions as weighted directed networks. Denote by $W_h = (\omega_{ij,h})$ the matrix containing all individual elements $\omega_{ij,h}$. Each element of W_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 , $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}$ in general. 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:

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

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:

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

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

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

In total there are $\frac{N(N-1)}{2}$ net pairwise directional connectedness measures, and N net total directional connectedness measures.

Finally, the total connectedness measure for the network of cryptos is the grand total of the off-diagonal elements 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 mean degree of the network. The larger the mean degree, the greater the overall network connectedness.

In the following, we will use this methodology to analyse in detail the network connectedness of cryptocurrencies, identify important spillover transmitters, and estimate the total connectedness of the system.

3 Data and Empirical Analysis

In the first step, for this empirical analysis, data was collected from the Coinmetrics.io website. We first selected the 500 cryptocurrencies and tokens having the largest market capitalization by January 2021. As this is at the end of the sample period, the resulting selection could be due to survivorship bias, which we acknowledge as a potential limitation of our methodology. We include assets of various characteristics such as consensus mechanism or utility. On the basis of these assets, we excluded the ones that were introduced after 2018, as the necessary amount of historical data would be too short to reliably estimate time series models. Also, we discarded cryptos that disappeared after a while, and those with consecutive missing values of more than ten days. Our sample period is from November 11, 2018 to February 16, 2021, so that each NVT series comprises 825 observations. Table 4.1 reports the finally selected 39 cryptocurrencies including symbols, market capitalizations (MCs) and rankings. Hence, we extract $N = 39$ cryptocurrencies of the 500 largest cryptocurrencies by market capitalizations which have been publicly traded for at least two consecutive years and whose NVT ratio is provided by coinmetrics.io.

Figure 3.1 shows the daily NVT series for six selected cryptocurrencies.

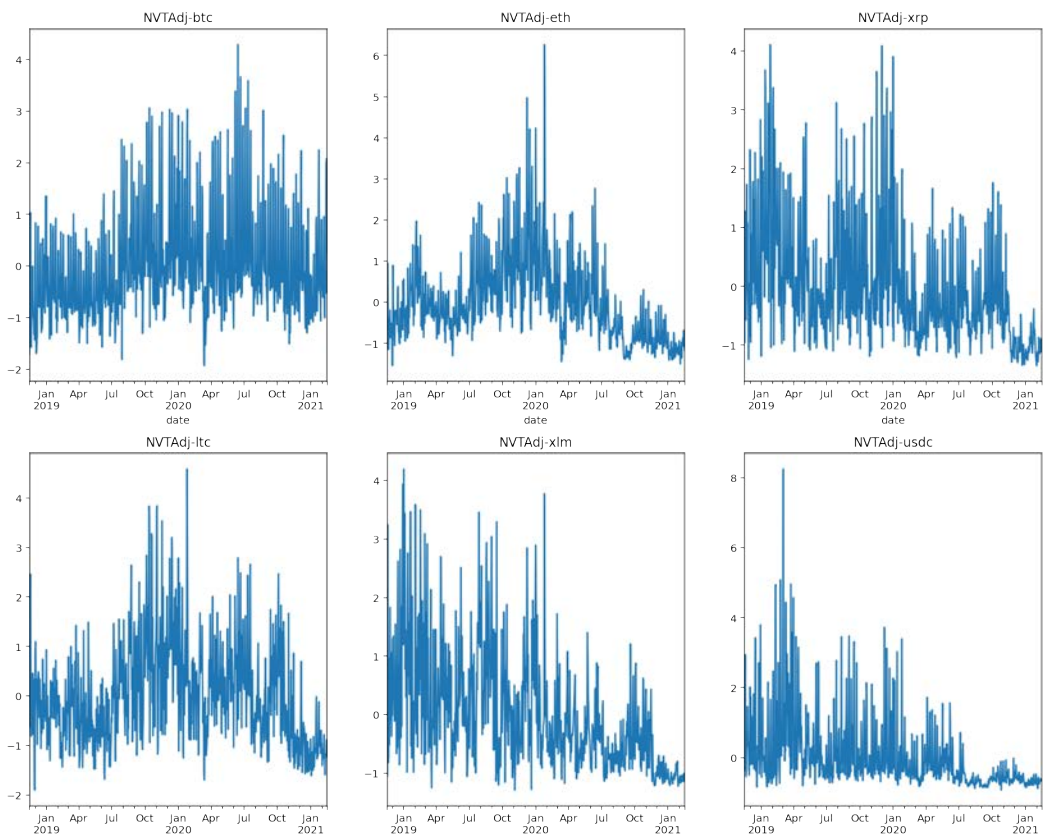

Figure 3.1: Evolution of NVT ratio for six cryptocurrencies from November 2018 to February 2021

In terms of missing values, there was only one value missing for Verge (xvg), which we imputed by the median. We show in Table 4.2 the descriptive statistics of the daily NVT series for the cryptocurrencies during the entire period. To save space, only the statistics for the 26 largest cryptos are reported.

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, for Huobi Token (ht), the mean is equal to 7722.28 while the median is equal to 1039.16. We would also like to highlight the enormous differences in levels between the medians for each cryptocurrency. For example, the NVT median of USD Coin(usdc) and Stellar (xlm) are equal to 6.81 and 899.69, respectively.

We can observe that Bitcoin, ethereum, Tether(usdt), USD Coin (usdc), Bitcoin cash(bch), and Zcash (zec) have the lowest volatility compared with other cryptocurrencies, confirming their status of relatively mature assets. Low volatility is of course an inherent feature of stablecoins such as Tether (usdt) and USD Coin (usdc). On the other hand, we see that the volatility of the NVT series Huobi Token (ht), Synthetix (snx), Augur (rep), Aragon (ant) and Gnosis (gno) is extremely high.

Figure 4.3 shows the correlation matrix of the adjusted NVT series. 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 strongly correlated with each other. On the other hand, the "small cap" cryptocurrencies such as gas and elf have a very low correlation with other cryptocurrencies. Moreover, we can observe that there are some large cap and medium cap cryptos 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 (large cap), and Basic Attention Token(bat), Decentraland(mana), 0x (zrx) and OMG Network(omg) from the second one (medium cap).

To detect whether or not there is seasonality in the adjusted NVT series, we have checked their autocorrelation function (ACF). Figure 4.3 shows different ACF plots for 9 selected cryptocurrencies. A weekly seasonality pattern is clearly distinguishable for all selected series. We use a seasonal adjustment for each series to filter out the seasonality, and the adjusted time series are shown in Figure 4.2.

We tested stationarity by using an Augmented Dickey-Fuller test for each time series, the results of which are reported in Table 4.3. We find that the vast majority of adjusted NVT series is stationary. For nine series, the null hypothesis of a unit root is not rejected at the 5% level, but this may be due to low power of the ADF test. We therefore continue to use these series without any further adjustments.

3.1 VAR-LASSO

To select the order of the VAR model, we use the smallest lag K such that the residual correlations does not show any significant serial correlation, using a multivariate portmanteau test of order ten, see Lutkepohl (1995). This results in a lag order of $K = 3$. Using VAR with large samples (39 cryptocurrencies) will lead to over-parameterization, as the VAR model has $K(N^2 + 1)$ parameters. In our case, we end up with 4335 regression parameters. Therefore, we use the least absolute shrinkage and selection operator (LASSO) method to reduce the dimensionality. We then estimate the model by minimizing equation by equation the LASSO criterion to shrink some of the parameters to zero. To find the optimal penalty parameter, we used five-fold cross-validation (CV). Figure 4.4 shows the estimated coefficients, where a large number has been shrunk to zero. We see that all NVT series are mostly influenced by their own lagged values, but there are quite a few lagged cross-terms that appear important. These spill-over effects are what we are looking at in the variance decompositions.

In terms of model diagnostics, we first started by checking the serial correlation using Ljung-Box test of residual autocorrelation, and the results of this test is shown in Table 4.4. The results indicate that we have just two cryptocurrencies whose residuals do show signs of serial correlation (Aelf(elf), and gas), which from a global perspective appears acceptable given the level of the test.

Second, we applied a normality test using the Jarque-Bera test to check the residual distribution, see Table 3.1. The test clearly rejects the null hypothesis of a Gaussian distribution at a 5% significance level. This confirms the pertinence of an ICA approach for the identification of structural innovations, as this requires nonnormality of the data.

Table 3.1: Normality test using Jarque-Bera

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

The correlation matrix of the residuals is shown in Figure 4.5. Clearly, there are some strong correlations in the residuals, and the correlation tends to be higher among the large cryptocurrencies, based on their market capitalization. For example, there are higher correlations between bitcoin, ethereum and Ripple than between smaller ones such as gas, fun, or gno.

3.2 Forecast error variance decomposition

We now proceed to the forecast error variance decomposition of the estimated VAR-LASSO model. The first step is to orthogonalize the residuals. We then use the FastICA algorithm in python, which maximizes the discrepancy from Gaussianity of the projected residuals in order to recover the structural innovations which are statistically independent.

We considered estimating network connectedness at the forecast horizon $h = 10$, which can be considered a medium term horizon. However, longer horizons would essentially yield the same results, as the variances have converged almost to the unconditional (long-term) error variances at horizon $h = 10$, due to the low persistence in the estimated VAR(3) model.

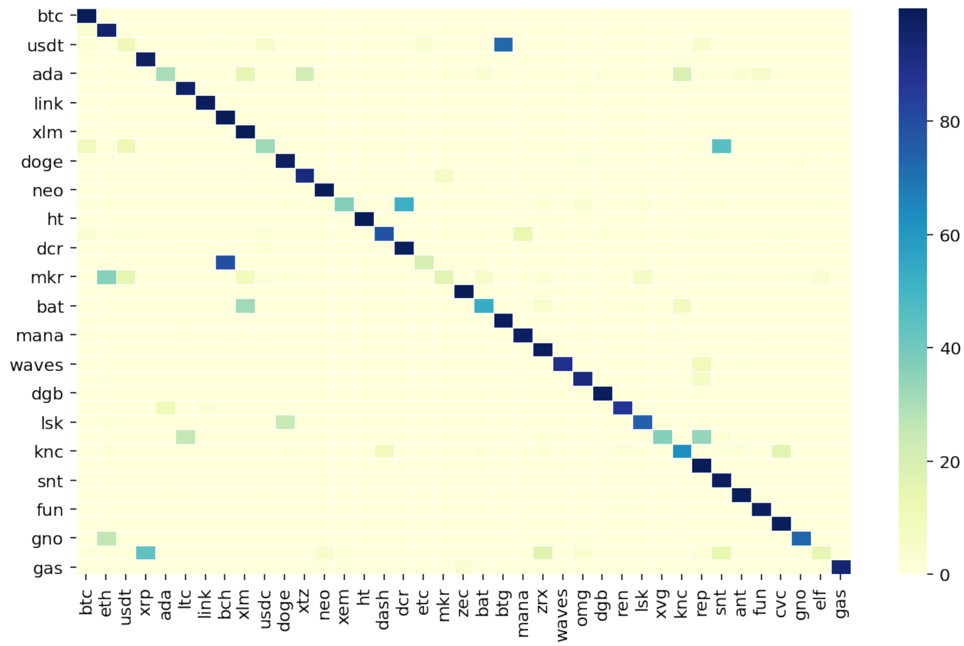

Figure 3.2: Heatmap that explains the NVT connectedness table for cryptocurrencies

The heatmap of the proportion of forecast error variances explained by other cryptos, W_h, is shown in Figure 3.2. We first discuss the diagonal elements, most of which are above 70%. This means that by far the largest proportions of NVT forecast error variances are explained by the own history of each NVT series. This is not surprising, as the most important and significant elements of the estimated VAR parameter matrices are the diagonal ones.

We now discuss the off-diagnonal elements of W_h which represent the pairwise directional connectedness. We observe that there are some cryptocurrencies that are significant transmitters of this network connectedness. For example, we see that the innovations to bch explain 27.906% of the error variance in forecasting btg's NVT value ten days ahead. Moreover, it contributes 24.516% of explaining the error variance in forecasting Ethereum(etc)'s NVT value ten days ahead.

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 only 0.07%, so that 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 only 0.001%. Thus, there is a strong net spillover in NVT from Cardano to ant. Furthermore, the innovations to snt contribute 19.197% of the error variance in forecasting ten days ahead of neo's NVT value. And it contributes 25.988% of the error variance in forecasting 10 days ahead of (elf)'s NVT value.

Table 3.2: 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

Table 3.2 contains the off-diagonal column and row sums of the connectedness matrix W_h, which are contributions to others and contribution from others, respectively. The row sum is 100%, so that the NVT connectedness from others is equal to 1 minus the diagonal element. We also report 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 %, and elf with 48,268% which means that these are the cryptocurrencies with NVT that receive from others much more than what they contribute to others. From a risk management perspective, one should be aware of a higher risk associated with these assets, as their NVT is highly influenced by shocks in other cryptocurrencies.

We can also identify from this table the cryptocurrencies with the smallest risk of being influenced by shocks to other cryptocurrencies: Cardano(ada) with a contribution from others of only 0.07% , ht with 0.07%, dash with 0.027%, snt with 0.003% and link with 0.012%.

What distinguishes Chainlink (link) from other cryptos is that it is one of the smallest recipients of network connectedness (0.012%), but also the smallest transmitter of shocks. It is therefore isolated in the system.

On the opposite side, the cryptocurrencies that have the largest contributions to others are omg with 72,479%, bch with 55,3%, snt with 50,04%, and doge with 45,87%. We also observe that Bitcoin, although being by far the largest crypto by market cap, does not generate widespread connectedness since it has a small contribution in transmitting NVT shocks to other cryptocurrencies (2.43%), and it also receives a small proportion of NVT spillovers from other cryptocurrencies (2.96%).

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 variances is due to spillovers from other cryptos.

3.3 Network Connectedness

We now represent the estimated networks graphically using several devices. These devices include the node's naming convention, node's size, node's color, and the direction of the edges. The node's naming convention is short for each cryptocurrency, node's size indicates either the from-connectedness or to-connectedness. We tried to specify different characteristics of cryptocurrencies based on the node's color: for each network it either indicates the size of their relative market capitalization, or the consensus mechanism that have been used.

Note that the edges whose NVT pairwise directional connectedness or spillover from one cryptocurrency to another are 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.

3.3.1 Based on the market capitalization

To specify the cryptocurrencies based on their market capitalization, we divided them into several ranges according to the size of their market capitalization. We first investigate the "to"-connections and then the "from" connections. Note that there is potentially an asymmetry: there may be assets that are important contributors, i.e. have strong "to"-connections, while being less important receivers, and vice versa. Figure 3.3 shows the network "to"-connections, which indicates that the NVT connectedness among cryptocurrencies does not necessarily depend on their size: Bitcoin is only a small transmitter, while some other mega-cap cryptocurrencies are high transmitters such as Cardano (ada), Litecoin, Bitcoin cash, Doge coin and neo. We see that there are also some cryptocurrencies whose market capitalization is between 1 and 2 billion USD are high transmitters such as Ethereum(etc), mana, 0x(zrx) and especially OMG network, which has received little attention in the literature, although it appears to be strongly linked to other assets. In addition, other cryptocurrencies with low market capitalization (below 500 million USD) such as Status(snt) and Civic(cvc), are more likely to propagate NVT shocks to others.

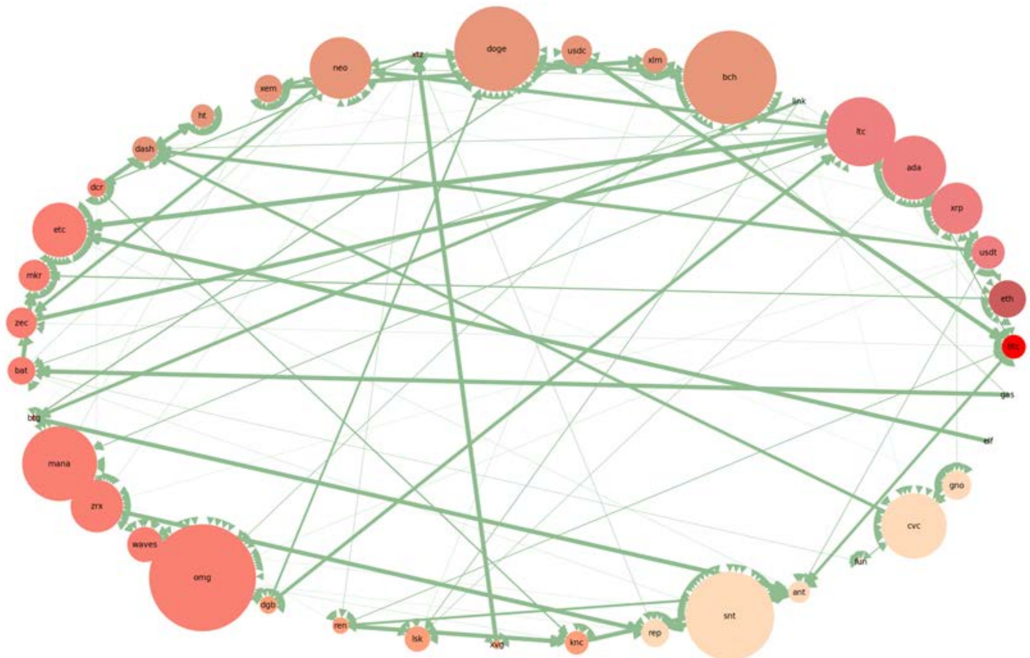

Figure 3.3: Connectedness network linking 39 cryptocurrencies based on their contribution to others. The colors indicate the market capitalization: red for more than 800 billion USD, indianred for more than 100 billion USD, lightcoral (between 10 and 100 billion USD), darksalmon (between 2 and 10 billion USD), salmon (between 1 and 2 billion USD), lightsalmon (between 500 million and 1 billion USD), and peachpuff (below 500 million USD).

It should be emphasized that bitcoin is not the dominant source of 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, many cryptos with low market cap affect the forecast error variance of cryptos with high market cap. For instance, DigiByte(dgb) is a big transmitter of shocks to ltc, elf to etc, and gas to bat.

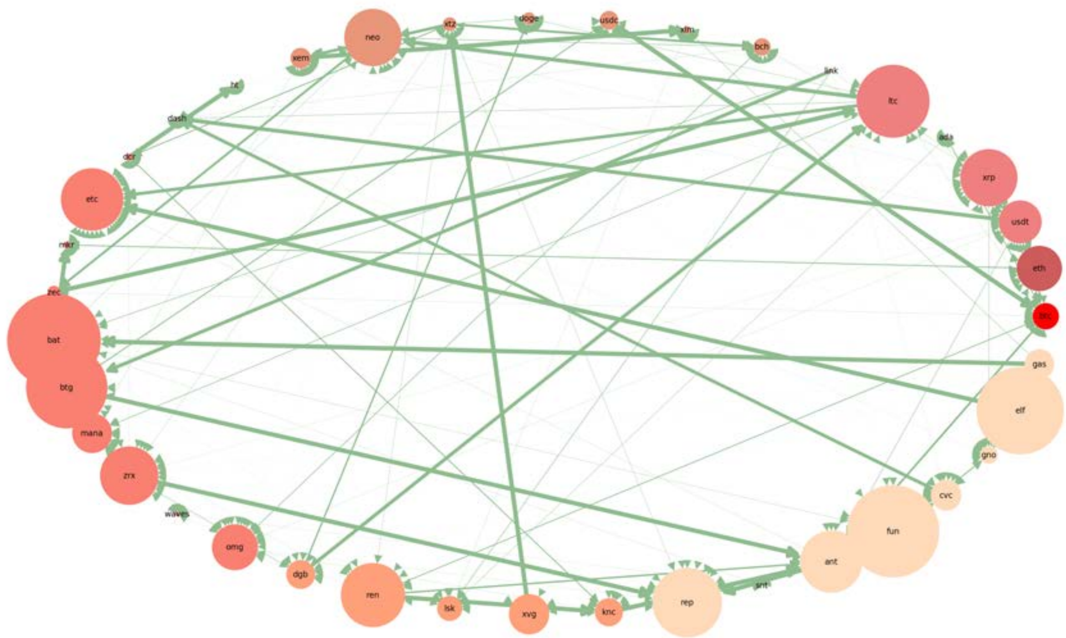

Figure 3.4: Connectedness network linking 39 cryptocurrencies based on the their market capitalization and their contribution from others.

We now consider the network constructed using the "from" connections between cryptos, see Figure 3.4. 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, for example: 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 can be explained to a large extent by 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.

3.3.2 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. 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 being Proof of Work (PoW) and Proof of Stake (PoS). PoW refers to an agreement algorithm that proves that it has completed a numerically difficult task that can easily be checked. Many cryptocurrencies rely on it such as bitcoin, dash, and doge. The main drawback of PoW is the amount of energy needed to achieve the numerical task. Therefore, many altcoins are using PoS, see e.g. Saleh (2021) for a formal economic model for PoS, and the conditions under which PoS generates consensus. 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 the cryptocurrency. The market-leading coins using PoS are Cardano (ADA), Polkadot and Stellar (XLM). There is also Delegated Proof of Stake (DPoS) which is a popular evolution of the PoS concept, where users of the network vote and elect delegates to validate the next block. In our data we only have Lisk(lsk) that relies on DPoS. There are 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 their importance for the connectedness. Each color in the network representation in Figure 3.5 specifies one type of consensus mechanism.

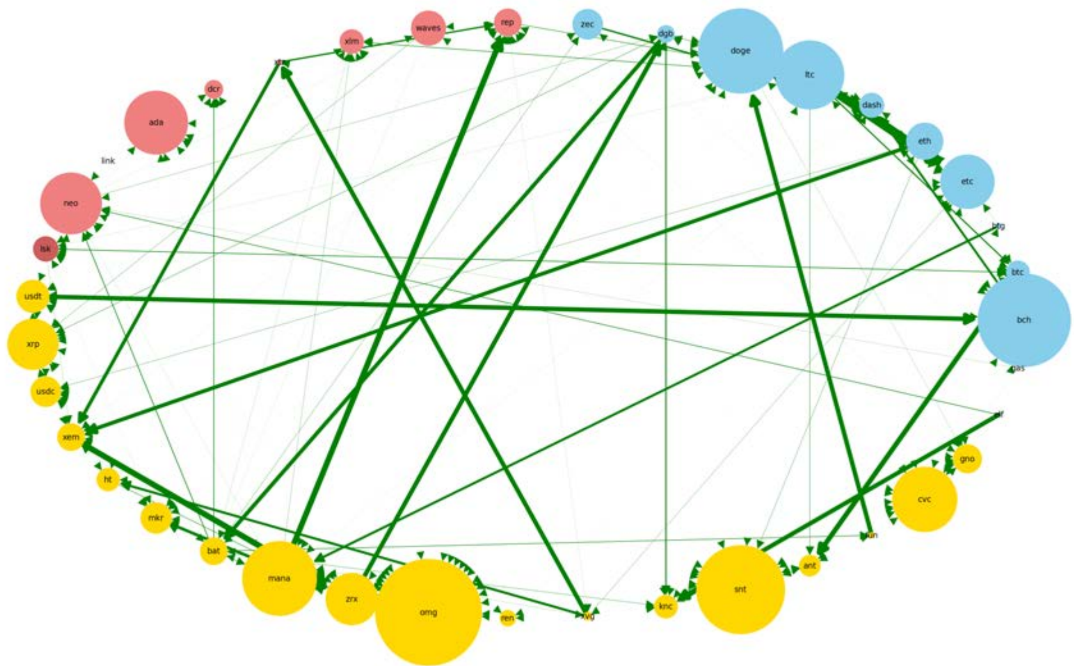

Figure 3.5: Connectedness network linking 39 cryptocurrencies based on the their consensus mechanism and their contribution in transmitting shocks to others. Each color specifies one type of consensus mechanism: PoW in blue, PoS in lightcoral, dPos in indianred, and the others are in yellow.

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: Bch, doge and ltc. 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. Both Cardano and neo are smart contract platforms that allow, for example, the development of decentralized finance applications.

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 the 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.

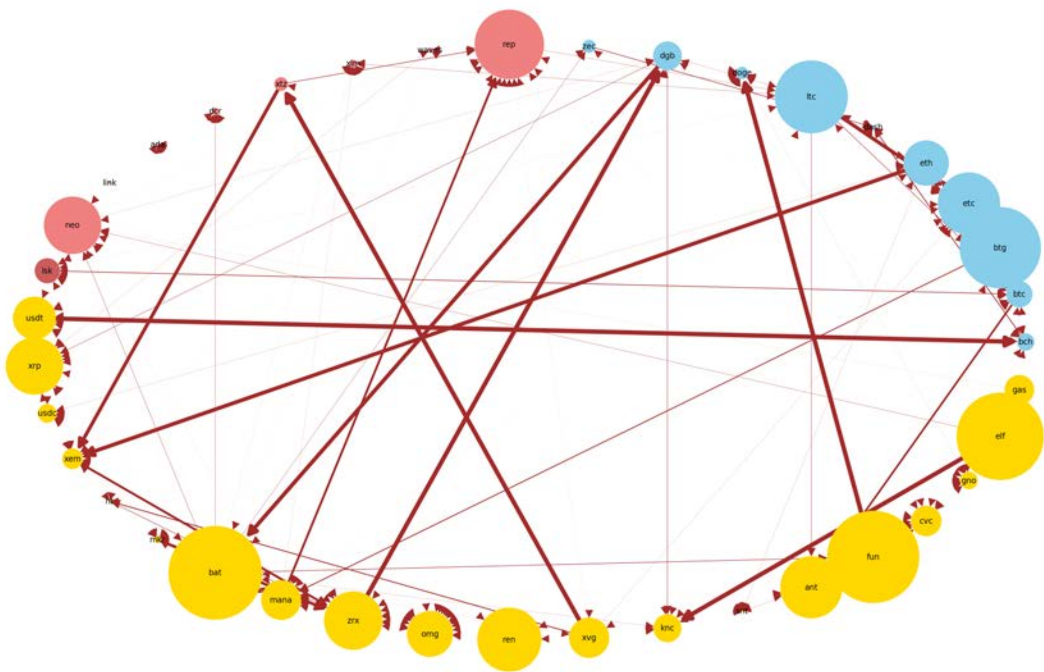

Figure 3.6: Connectedness network linking 39 cryptocurrencies based on the their consensus mechanism and their contribution in receiving from others

We now turn to the network based on the "from" connections, see Figure 3.6. We see that 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 that receive higher spillovers from other assets. We also observe that the highest pairwise directional connectedness values are coming from the cryptocurrencies that use consensus mechanism other than PoW and PoS: from mana to rep, from Tether(usdt) to Bitcoin Cash (bch). The highest transmitters and highest receivers are the cryptocurrencies that use consensus mechanism other than PoW and PoS.

Our results suggest 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. Since we also observe small contributions in transmitting shocks to others within cryptos that use Proof-of-stake, it means that these cryptocurrencies are less interconnected. From a risk management perspective, it may be beneficial to invest in cryptocurrencies based on PoS consensus mechanism. Moreover, using cryptos that use PoS is more energy efficient since it does not require highly complex computations compared to PoW.

3.3.3 Based on the purpose

Each cryptocurrency is used for a different purpose, for example security, payments, smart contracts, etc. Therefore, we finally distinguish different cryptocurrencies with respect to their utility, to see whether the connectedness is at least partially explained 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 decentralized financial services such as savings, loans, trading, and insurance to practically anyone with an internet-enabled smartphone. 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. Note that these categories are somewhat arbitrary and others may have been chosen, see e.g. Oliveira et al. (2018) for a more detailed study of the types and purposes of tokens.

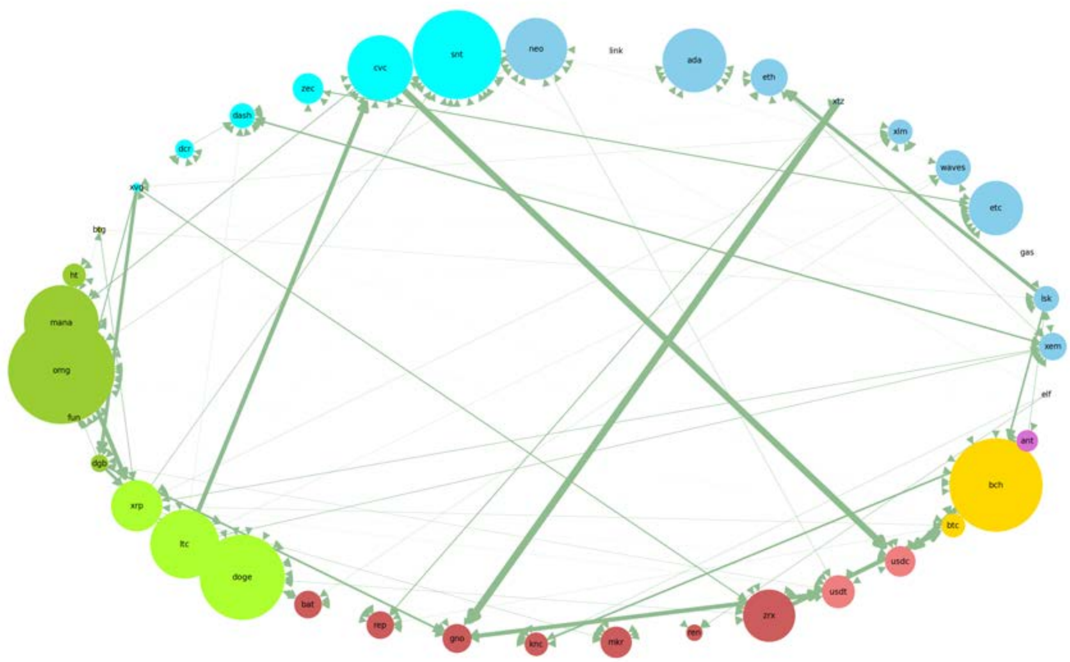

Figure 3.7: Connectedness network linking 39 cryptocurrencies based on their categories and their contribution to others: skyblue for smart contracts, indianred for deFi, aqua for privacy, greenyellow for medium of exchange, yellowgreen for payment, and orchid for enterprise solution.

The network based on "to" connections is shown in Figure 3.7, where each color specifies one category. 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. 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 DeFi cryptocurrencies 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).

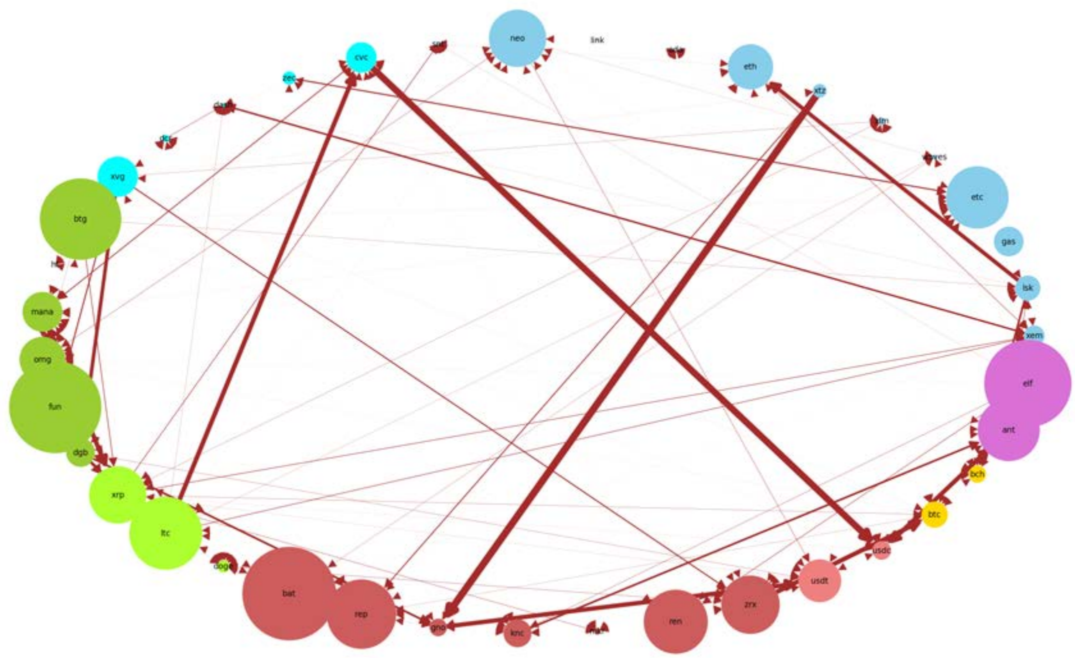

Figure 3.8: Connectedness network linking 39 cryptocurrencies based on the their categories and their contribution from others

Looking at the network based on "from" connections in Figure 3.8, 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 also small. This result indicates that the cryptocurrencies that are used for privacy are the least interconnected, and receive small spillovers from other cryptos. Similar to the consensus mechanism proof of stake, cryptos that are used for privacy appear less connected and hence beneficial to reduce risks in a diversified portfolio.

4 Conclusion

We have investigated the connectedness of cryptocurrencies via their network to transaction (NVT) ratio. The methodology uses the contributions of each asset, to and from other assets, to explain the variances of forecast errors ten days ahead.

One of our findings is that the NVT connectedness, or the 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, but also some small-cap cryptocurrencies are important transmitters of NVT shocks (e.g., cnt, cvc, omg, mana). More importantly, the largest emitter of NVT shocks in the cryptocurrency market is omg, which is small cap that offers scaling solutions for the Ethereum network and attracts little public attention.

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 in spillovers to altcoins. 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, which make them attractive from a risk diversification perspective. Moreover, using cryptos that use PoS is more efficient since it does not require high electricity costs and high material purchase costs to verify transactions. Similarly, we have found that the cryptocurrencies that are used for privacy are the least interconnected, and receive small spillovers from other cryptos, which make them attractive for risk management.

Our results are obtained using a particular methodology which, just as any methodology, has limitations. One of them is the use of a linear vector autoregression for NVT, which involves several choices such as the order of the model, linearity, and estimation method, that can be criticized. In the methodological part of the paper we have tried our best to justify our choices. Another potential limitation is our joint treatment of cryptocurrencies and tokens without explicitly taking into account the technical links between them, such as e.g. ERC20 tokens and Ethereum. Furthermore, when analysing spillover effects, we do not distinguish between effects that are caused by technical reasons and those that are not. Finally, as mentioned, our data could be affected by survivorship bias as the cryptos were selected based on market capitalization at the end of the sample period.

Our investigation complements the literature on the risks associated with cryptocurrencies and provides new information for market participants and risk managers. 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 dynamic framework, either using rolling-samples or a genuine dynamic analysis, in order to examine the cycles or trends, should they exist, in the connectedness measures. It may be that overall connectedness increases over time as markets become more integrated, or that individual assets become systemically risky in that they become highly linked with other assets at a given time. It would also be possible to use a dynamic independent component analysis as in Hafner and Herwartz (2021), that allows for time-varying rotations to construct the structural innovations of the model. We leave these important issues for future research.

Appendix

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

Cryptocurrency	Symbol	MC	Rank	Cryptocurrency	Symbol	MC	Rank
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				

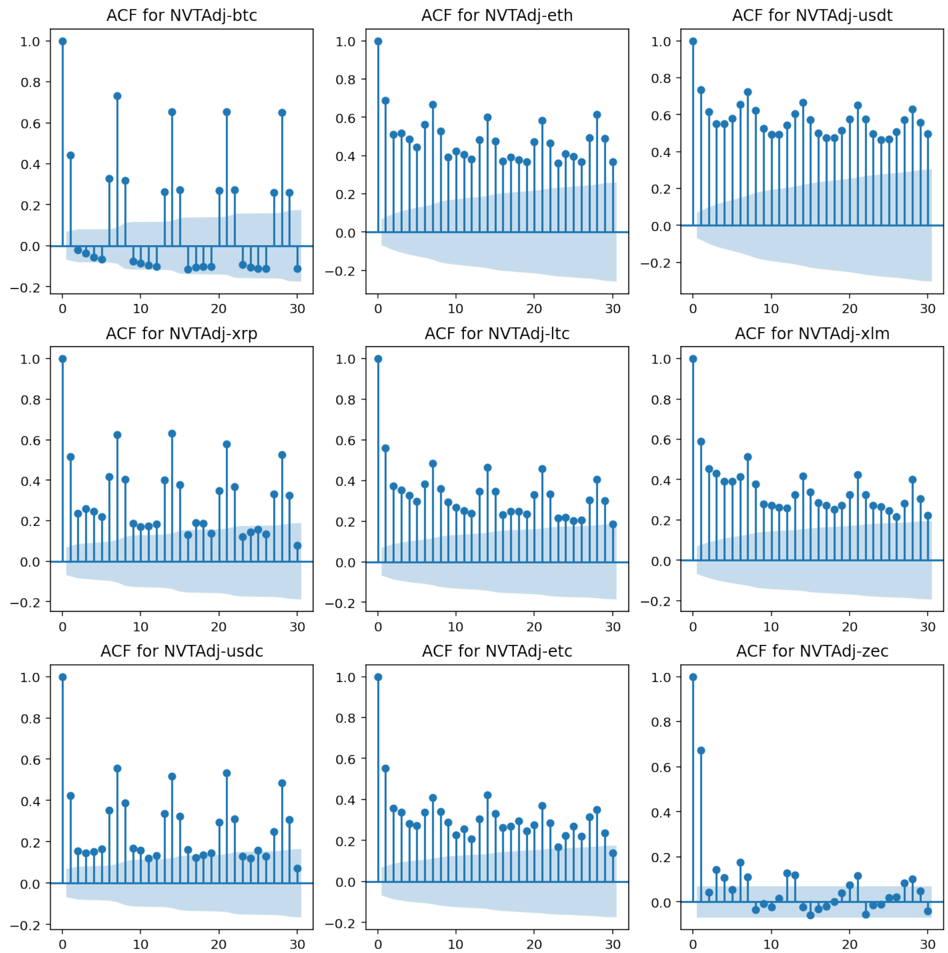

Figure 4.1: ACF plots for 9 NVT series

Table 4.2: NVT descriptive statistics 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

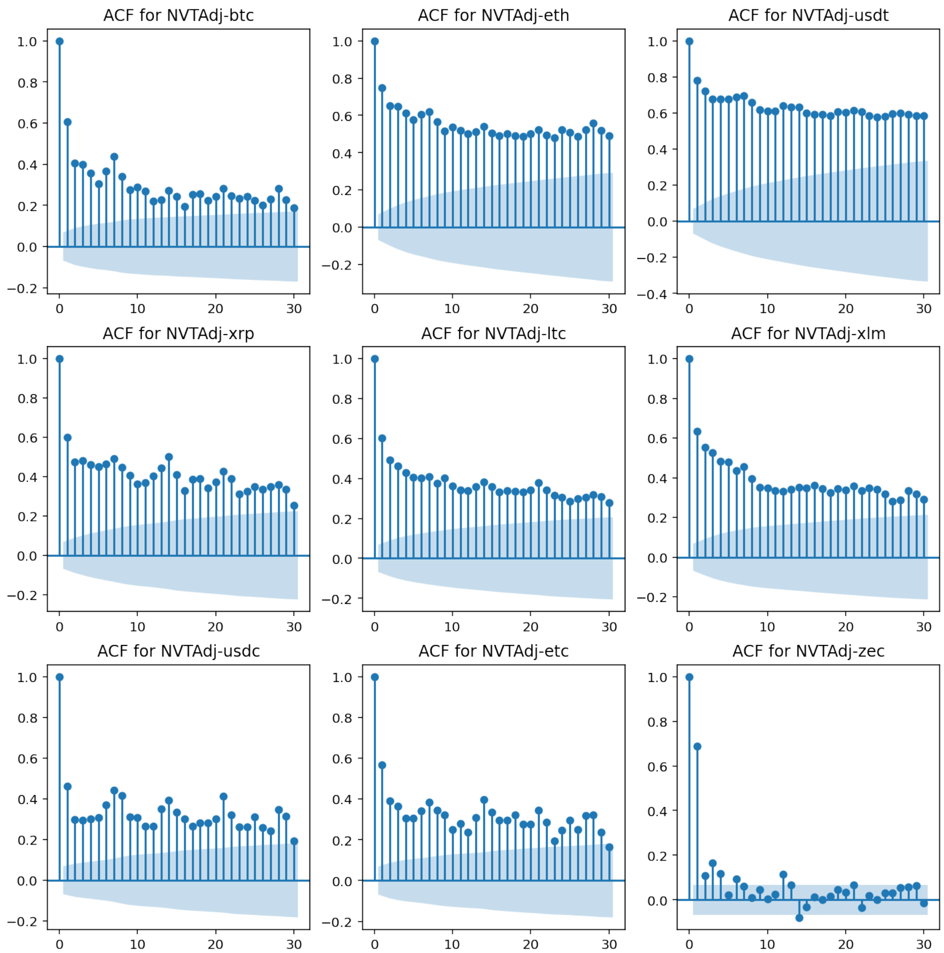

Figure 4.2: ACF plots of 9 NVT series after removing seasonality

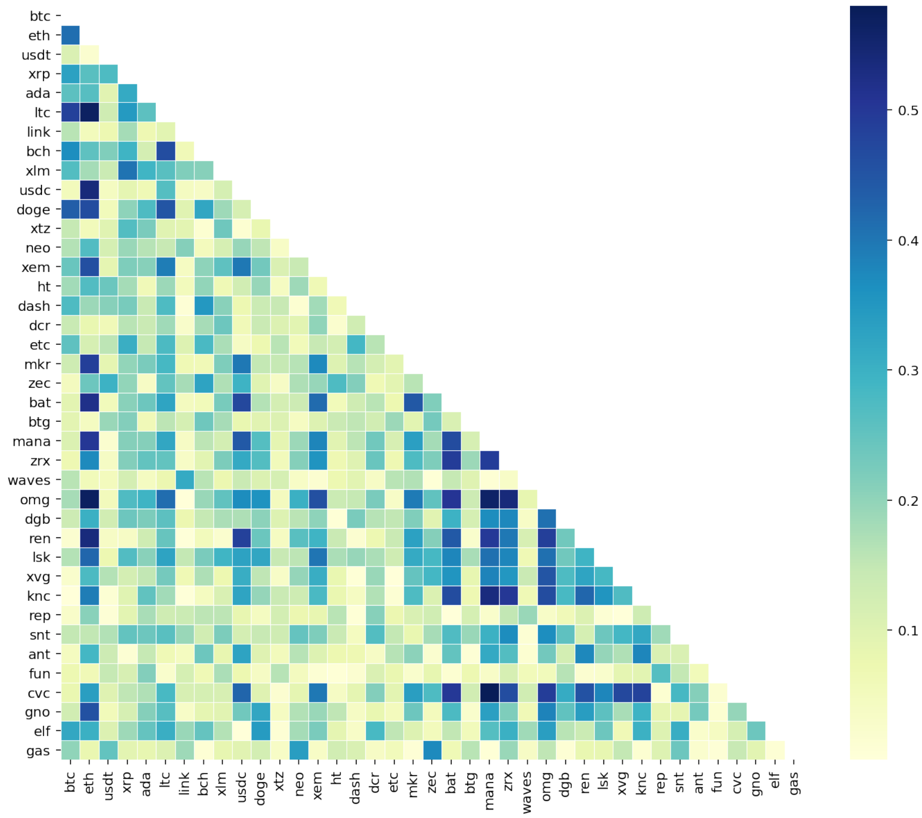

Figure 4.3: Correlation between different NVT ratios of cryptocurrencies

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

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

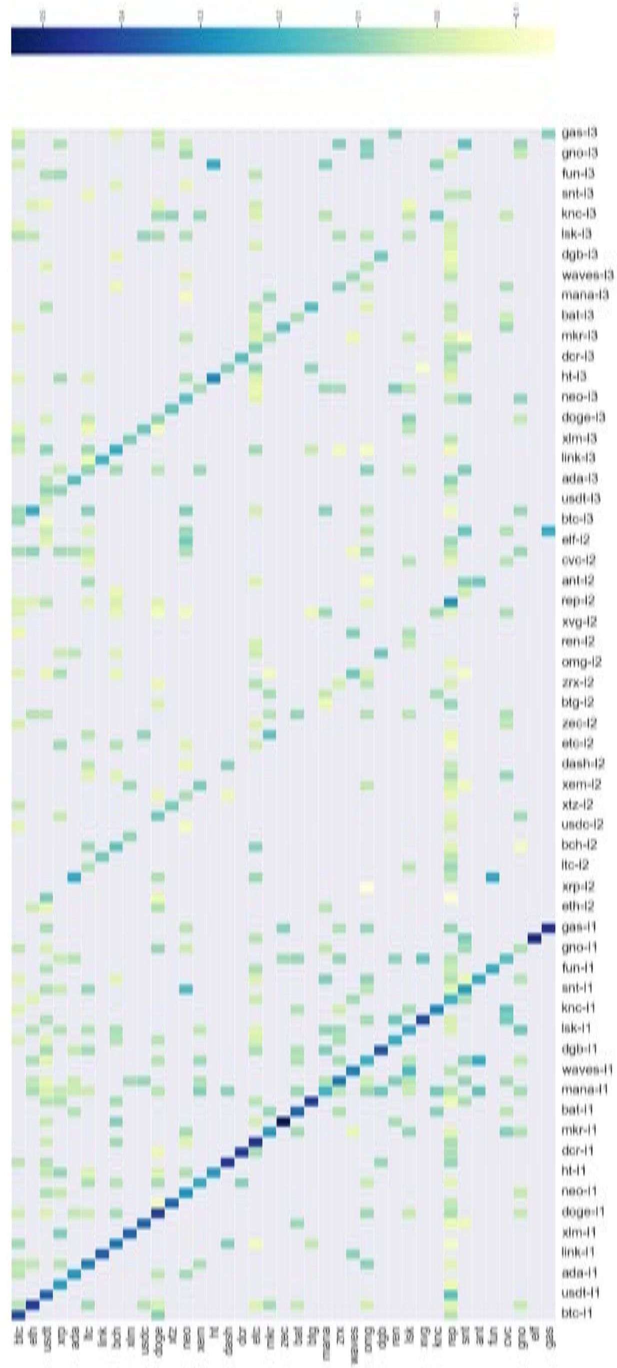

Figure 4.4: Estimated coefficients of the VAR(3)-LASSO model

Table 4.4: P_values for the Ljung-Box test on the residuals of the VAR-LASSO model

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

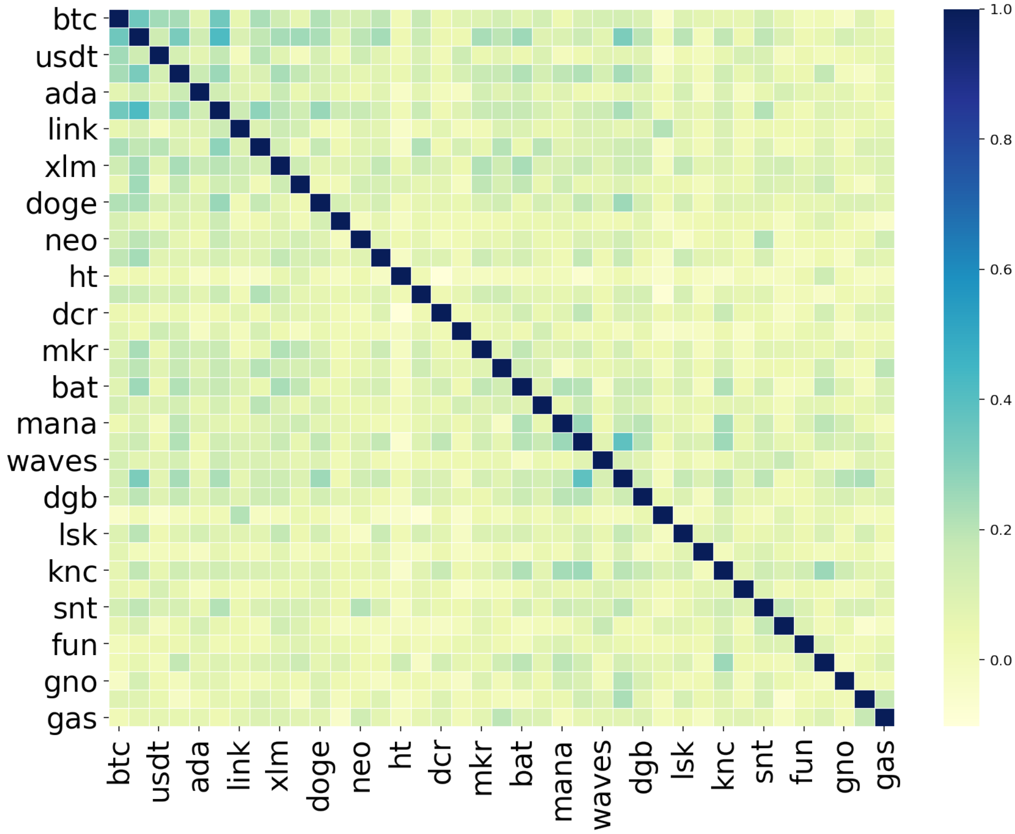

Figure 4.5: Correlation in the residuals of the estimated VAR-LASSO model

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