Analyzing Cryptocurrency Returns

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Abstract

Our project explores forecasting and analyzing relationships among cryptocurrency returns. We show that a VAR model forecasting multiple cryptocurrencies jointly outperforms more powerful non-linear univariate models. We also show multiple results regarding structure analysis on the VAR model, comparing the orthogonalized impulse responses and generalized forecast error variance decomposition for each cryptocurrency.

1 Introduction

Since Bitcoin's inception in the year 2009, popularity of cryptocurriences has exploded. Once a niche, relatively-unknown topic, cryptocurriences are now prominently featured throughout the mainstream media. Similar to the Gold Rush and the Dot-Com boom of the early 2000s, most view cryptocurrencies as a way to strike it rich. Bitcoin's frequent price surges have been well-documented, as just in the last year the price has risen by over $50,000 dollars. As cryptocurrencies continue to produce profits and flood the markets, it is a very lucrative question to ask if one can understand their behavior.

This project aims to tackle two main questions: how can we forecast cryptocurrency returns and what are the dependence relationships among them? As mentioned before, it is easy to imagine why we might want to be able to forecast returns. But in order to do this, we can leverage the pair-wise correlations between cryptocurrencies. Better understanding this network of relationships has two large benefits. Firstly, it can provide more information for our forecasting models to utilize. Secondly, it can help us better understand the risk and diversification of a portfolio containing these assets.

2 Background

Most prior work either compares more traditional time series methods to machine learning models or solely look at using ML-based models to forecast prices and returns. ML-based models have mostly been shown to outperform them. "...Independent of the period under analysis... and method, ML models present high levels of accuracy and improve the predictability of prices and returns of cryptocurrencies, outperforming competing models such as [ARIMA] and [EMA]" [3]. Persson et. al. investigated [2] using a Residual Recurrent Neural Network (R2N2) that showed significant improvements over ARIMA-type models.

As for analyzing the relationships between cryptocurrencies, Qiang et. al. [1] investigated several properties related to the six largest cryptocurrencies by market capitalization at the time (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash). Their primary contribution was quantifying spillover effects across these currencies. They conclude that Litecoin along with Bitcoin are at the center of

Submitted to 34th Conference on Neural Information Processing Systems (NeurIPS 2020). Do not distribute.

returns, and the second-largest cryptocurrency Ethereum is only a recipient of spillovers effects (as opposed to a contributor such as Litecoin).

The most recent data from their dataset was February 22, 2018, while the earliest data in our dataset starts on January 1st, 2018. As the market surrounding cryptocurrencies has vastly changed in just a few short years, it is possible that the relationship dynamics have also changed, especially when considering the influx of many new competing cryptocurrencies. They primarily used the generalized forecast-error variance decomposition (FEVD) to quantify their metrics of connectedness.

3 Methods

3.1 Models

The univariate modeling methods used were primarily based on the ARIMA-type models covered in class. We used a VAR model to forecast the cryptocurrency returns jointly and a large number of different linear and nonlinear univariate model structures to forecast individual cryptocurrency returns.

3.1.1 Self-Exciting Transition Autoregressive (SETAR)

In financial markets, stock index has been observed to exhibit different characteristics under different states of economy, (e.g. during high volatility during recession). Therefore, adopting a model that can switch smoothly from one scenario to another could theoretically improve performance. Self-Exciting Transition Autoregressive (SETAR) models find a threshold variable Z_t which determines which fitted linear model to use:

$$X_{t+m} = \begin{cases} \phi_1 + \phi_{10} X_t + ... + \phi 1 p X_{t-p} + \epsilon_{t+s} & Z_t \leq c \\ \phi_2 + \phi_{20} X_t + ... + \phi 2 p X_{t-p} + \epsilon_{t+s} & Z_t > c \end{cases} \tag{1}$$

Thus SETAR models can potentially explain nonlinear dynamics of financial time series, although empirical studies provide mixed results for these types of models [4]. We also used the generalized version Logisitic Smooth Transition Autoregressive (LSTAR), which uses a logistic function to weight the use of the two models depending on the value of the threshold variable.

3.1.2 Additive Autoregressive Model (AAR)

The non-parametric Additive Autoregressive Model (AAR) model (or GAM) took the form

$$x_{t+m} = \mu + \sum_{i=1}^{p} s_i(x_{t-i-1})$$

where s_i are smooth functions represented by penalized cubic regression splines.

3.1.3 Neural Network

The neural network model used was very basic compared to deep, more complicated models that would be more effective. We used a simple version implemented in the nnet R package for ease of use. The forecasts are defined as:

$$x_{t+s} =_0 + \sum_{j=1}^{D} {}_j g(\gamma_{0j} + \sum_{i=1}^{m} \gamma_{ij} x_{t-i-1})$$

where D is the number of hidden units, and g is the activation function.

3.2 Structural Analysis

For the structural analysis, we first fit a VAR model to the data. Explicitly this is modeled as

$$Y_t = A + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + A_p Y_{t-p} + u_t$$

where $p = \#$ of lags, $k = \#$ of time series, $A \in R^k$, $B_j \in R^{kxk}$, and $u_t \in R^k \sim WN(0, \Sigma_\omega)$.

We can then perform structure analysis on the model. We are interested in this because, unlike in the univariate case, there is a bidirectional relationship between all of the variables (i.e. the prediction of variable x depends on variables whose values also depend on x). With this interconnectedness comes a price though. Individual coefficient estimates provide limited information on the reaction of a system to a change since all the variables depend on one another. This motivates us to look at the impulse response function (IRF), which measures the effects of a shock to a variable on a variable.

When we transform our VAR(p) process into its infinite moving average process, we can derive the values for this function as Φ_i where

$$Y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-1}$$

The only issued posed by this formulation is that we are unable to reason about instantaneous relationships between variables. One solution is to compute the orthogonalized impulse responses (oIR), where we decompose the error covariance matrix Σ_ω into a lower triangular matrix L with positive diagonal elements. We accomplished this by taking the Choleski decomposition.

$$\Sigma_\omega = LL^T$$

We can also examine the Forecast Error Variance Decomposition (FEVD), which decomposes the variance of the forecast error into the contributions from specific external shocks. This allows us to see how important a shock is in explaining the variations of the variables in the model. Here we calculate the generalized FEVD as discussed in Qiang et. al. [1].

4 Experiments

We computed basic summary statistics for each cryptocurrency to compare and contrast them.

	Binance Coin	Bitcoin	Bitcoin Cash	Cardano	Dogecoin	EOS.IO	Ethereum	Ethereum Classic	IOTA	Litecoin	Maker	Monero	Stellar	TRON
Mean	3.183935e-05	-1.559993e-06	-4.636348e-06	1.766035e-06	4.236218e-05	-1.235018e-06	-1.569049e-06	3.745601e-05	1.619966e-05	-1.381606e-05	-2.475019e-06	7.652283e-06	-1.020357e-05	9.131856e-06
Variance	2.972191e-05	4.055206e-06	4.196183e-05	2.034111e-05	6.596995e-05	2.329647e-05	6.227767e-06	8.051281e-05	6.432225e-05	1.262420e-05	3.596191e-05	4.426824e-05	2.715928e-05	2.422917e-05
Skewness	1.138876e+00	1.429658e+00	3.423190e+00	2.409741e-01	2.296246e+00	8.170746e-01	6.970623e-01	1.270059e+00	3.821637e-01	1.436972e+00	7.120396e-01	2.978419e-01	1.092518e+00	1.188936e+00
Kurtosis	1.072900e+02	6.883791e+01	3.849582e+02	3.358373e+01	1.058000e+02	4.709867e+01	7.885892e+01	1.229667e+02	2.990081e+01	6.674963e+01	3.038574e+01	6.413195e+01	4.284071e+01	5.935696e+01

As we would expect, all of the cryptocurrencies meet the standard definition of being "fat-tailed". Every cryptocurrency's kurtosis is greater than 1, indicating that it has a wide tail. Most of the currencies are also heavily skewed, indicating by their large skewness (third moment) values.

4.1 Univariate Model

We first looked at univariate models for each currency to determine what type of SARIMA model is most appropriate. Shown here is our analysis on Bitcoin returns. To decide on a model, we first checked that the dependent variable was roughly stationary (which it was since the target is already the log-transformed returns). We then inspected the ACF and PACF plots, as shown below.

The cyclical structure of the PACF plot indicates a seasonal component to the series. Inspecting the ACF plot, we see that it cuts off at lag $1s$ (s = season = 15). The PACF tails off at lags $1s$,$2s$,... . This implies an SMA(1), $P = 0$, $Q = 1$, in the season ($s = 15$).

We then look at the non-seasonal component. The ACF tails off but the PACF cuts off at lag 3 or 4. We tried fitting both an ARIMA(3,0,0) x (0,0,1)_15 and ARIMA(4,0,0) x (0,0,1)_15 and forecasted the next 30 observations on a held-out test set.

After fitting both models, we found that all of the coefficients are statistically significant (but this could easily be due to the immense size of our data). The standardized residuals looked approximately like white noise. The ACF of the residuals exhibited no large values or obvious pattern. The only suboptimal diagnostic is that the QQ-plot showed a large departure from expected normalitity. The AR(3) model performs slightly better than the AR(4) model in all of the AICc, AIC, and BIC metrics

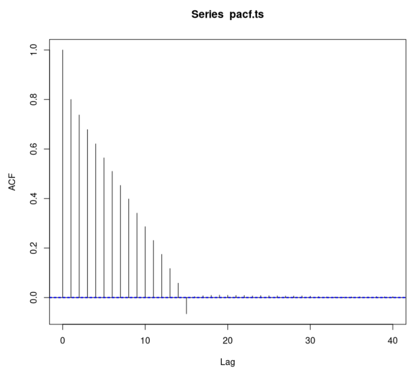

Figure 1: ACF plot for Bitcoin returns

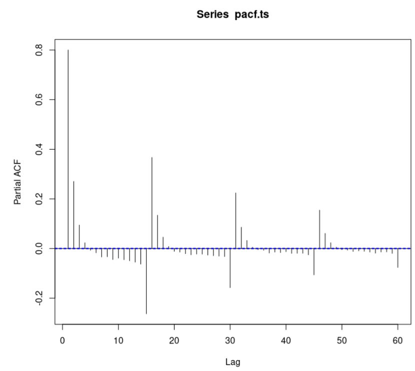

Figure 2: PACF plot for Bitcoin returns

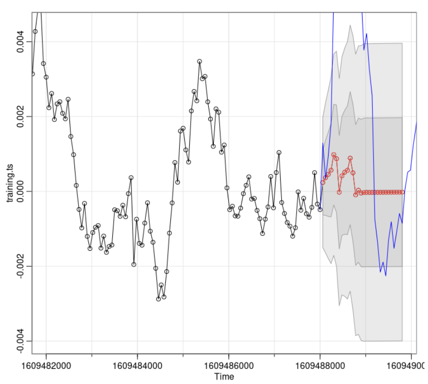

Figure 3: Seasonal AR(3) model for Bitcoin returns

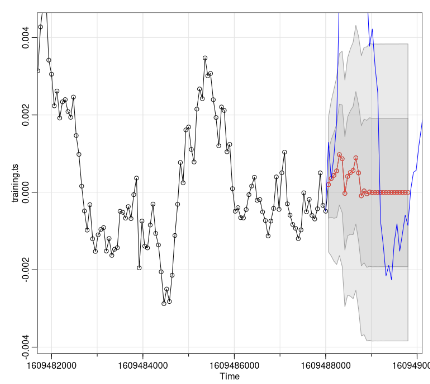

Figure 4: Seasonal AR(4) model for Bitcoin returns

4.2 Causality Analysis

We next fitted a VAR model using multiple cryptocurrencies to predict the target returns. There were several different configurations of the data to test different aspects. We ran analyses on datasets with samples from only three times per day and samples from every five minutes. We also split the data into two subsamples - data before the creation of Dogecoin (pre-Doge) and data after the creation of Dogecoin (post-Doge). Our sample sizes were large enough that we felt there was little loss in splitting the data yet we could analyze if Dogecoin had any effects on the dynamics of the cryptocurrency market. Across both datasets we included Cardano, Stellar, Ethereum, Bitcoin, Binance Coin, and Litecoin. In order to draw conclusions about casuality between the cryptocurrencies, we utilized two common methods: Impulse Response (IR) Analysis, and Forecast Error Variance Decomposition (FEVD).

4.2.1 Impulse Response Analysis

We first inspect the analysis of the 3-daily dataset. Since Orthogonal Impulse Response Analysis (oIRA) depends on the ordering of the predictors, we ran the analysis on two different orderings. The first was ordered by market cap, with Ethereum and Bitcoin being the last cryptocurrencies under the hypothesis that they would have the most effect on all other cryptocurrencies. The second ordering was chosen to have Ethereum and Bitcoin in the middle with Litecoin and Binance Coin at the end. All responses were computed on both the pre-Doge and post-Doge subsamples.

```
> ortho_no_doge
                  Cardano       Stellar  Binance.Coin      Litecoin      Ethereum     Bitcoin
Cardano       5.698473e-03  0.000000e+00  0.000000e+00  0.000000e+00  0.0000000000 0.000000000
Stellar       1.759604e-03  6.367694e-03  0.000000e+00  0.000000e+00  0.0000000000 0.000000000
Binance.Coin  1.659010e-03  1.056639e-03  4.971020e-03  0.000000e+00  0.0000000000 0.000000000
Litecoin     -1.407675e-04  5.812176e-05 -2.448732e-04  3.584929e-03  0.0000000000 0.000000000
Ethereum     -3.782010e-04 -2.895360e-04 -1.675385e-04 -3.044961e-05  0.0026298979 0.000000000
Bitcoin      -9.537067e-05  1.735227e-04 -1.722155e-05  9.860124e-05 -0.0001382203 0.001687873
> ortho_doge
                  Cardano       Stellar  Binance.Coin      Litecoin      Ethereum       Bitcoin    Dogecoin
Cardano       4.929620e-03  0.000000e+00  0.000000e+00  0.0000000000  0.0000000000  0.0000000000 0.000000000
Stellar       1.158150e-03  4.915792e-03  0.000000e+00  0.0000000000  0.0000000000  0.0000000000 0.000000000
Binance.Coin  4.361932e-04  5.179125e-06  4.652516e-03  0.0000000000  0.0000000000  0.0000000000 0.000000000
Litecoin     -3.095929e-05 -8.446236e-05 -1.533696e-04  0.0036401640  0.0000000000  0.0000000000 0.000000000
Ethereum     -1.969467e-04 -2.848951e-04 -1.635131e-04  0.0002908909  0.0023593197  0.0000000000 0.000000000
Bitcoin      -4.188793e-04 -2.312512e-04  3.420225e-05  0.0001635994  0.0002571024  0.0022549321 0.000000000
Dogecoin     -1.626570e-04  8.058125e-05 -1.948394e-04 -0.0012403999 -0.0012597760 -0.0005813688 0.007126421
```

Comparing the instantaneous responses pre-Doge and post-Doge, in every currency except Bitcoin the impulse response onto itself either stayed about the same or weakened. For example, when looking at the response of Ethereum to a shock in Ethereum, the response decreased by 10%. Cardano decreased by 13% and Stellar by 23%. The only currency this didn't hold for was Bitcoin, which saw a 25% increase.

One would think that the introduction of a new currency would create larger forces within the network, causing each currency to become less dependent on itself. A shock to Ethereum has less impact on Ethereum's future state with the introduction of Dogecoin. Why Bitcoin did not follow this pattern may be because of the unique nature of Bitcoin's changing status in the market. To this day, Bitcoin is arguably the only cryptocurrency well-known in the mainstream media. It arguably started becoming "mainstream" around our cutoff date of when Dogecoin was introduced in December 2019. Another possibility is that Bitcoin's dependency on itself was so low pre-Doge that it increased just by the nature of cryptocurrencies. Pre-doge Bitcoin had the lowest value at .00169, where the second-lowest was Ethereum at .00263. Post-Doge this grew to .00225, which was much closer to Ethereum's new value.

We can also see that after the instantaneous effect there was very little response to a shock, as the impulse response was near zero for any forecast two steps out or greater.

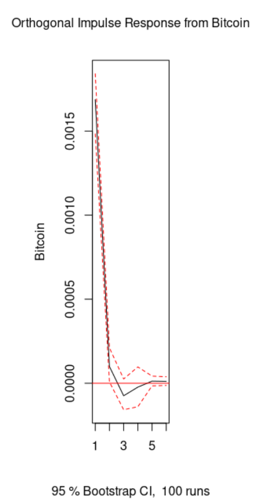

Figure 5: Bitcoin-Bitcoin orthogonal IR pre-Doge, 3-daily

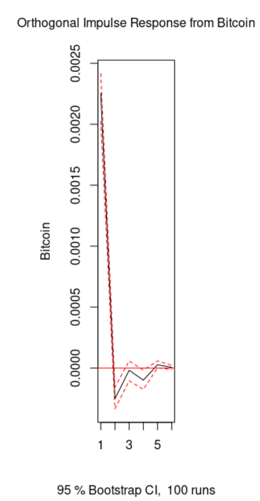

Figure 6: Bitcoin-Bitcoin orthogonal IR post-Doge, 3-daily

We also calculated the orthogonal impulse responses with different orderings, but found them to have neglible effects

```
                  Cardano       Stellar      Ethereum       Bitcoin  Binance.Coin    Litecoin
Cardano       5.698473e-03  0.000000e+00  0.000000e+00  0.000000e+00  0.0000000000 0.000000000
Stellar       1.759604e-03  6.367694e-03  0.000000e+00  0.000000e+00  0.0000000000 0.000000000
Ethereum     -3.782010e-04 -2.895360e-04  2.635405e-03  0.000000e+00  0.0000000000 0.000000000
Bitcoin      -9.537067e-05  1.735227e-04 -1.379759e-04  1.690859e-03  0.0000000000 0.000000000
Binance.Coin  1.659010e-03  1.056639e-03 -3.160186e-04 -7.641777e-05  0.0049603767 0.000000000
Litecoin     -1.407675e-04  5.812176e-05 -2.585334e-05  2.094370e-04 -0.0002438192 0.003578785
> ortho_doge
                  Cardano       Stellar      Ethereum       Bitcoin  Binance.Coin     Litecoin    Dogecoin
Cardano       4.929620e-03  0.000000e+00  0.0000000000  0.0000000000  0.0000000000  0.000000000 0.000000000
Stellar       1.158150e-03  4.915792e-03  0.0000000000  0.0000000000  0.0000000000  0.000000000 0.000000000
Ethereum     -1.969467e-04 -2.848951e-04  0.0023828016  0.0000000000  0.0000000000  0.000000000 0.000000000
Bitcoin      -4.188793e-04 -2.312512e-04  0.0002721938  0.0022593507  0.0000000000  0.000000000 0.000000000
Binance.Coin  4.361932e-04  5.179125e-06 -0.0003192658  0.0001088935  0.0046402708  0.000000000 0.000000000
Litecoin     -3.095929e-05 -8.446236e-05  0.0004549135  0.0002064569 -0.0001273197  0.003606735 0.000000000
Dogecoin     -1.626570e-04  8.058125e-05 -0.0013854182 -0.0006494473 -0.0002754342 -0.001041418 0.007126421
```

When we conducted the analysis on the five-minute dataset, almost all of the directions of the impulse responses stayed the same as in the 3-daily dataset; e.g. a shock to Cardano had a posive response to Cardano, a shock to Stellar had a negative response to Ethereum in both datasets.

```
> ortho_no_doge
                  Cardano       Stellar  Binance.Coin     Litecoin      Ethereum      Bitcoin
Cardano       0.0038176467  0.000000e+00  0.0000000000 0.000000e+00  0.000000e+00 0.000000000
Stellar       0.0011046273  4.823952e-03  0.0000000000 0.000000e+00  0.000000e+00 0.000000000
Binance.Coin  0.0007200358  8.530049e-04  0.0039513573 0.000000e+00  0.000000e+00 0.000000000
Litecoin     -0.0002633288 -9.922313e-05 -0.0002033944 1.994071e-03  0.000000e+00 0.000000000
Ethereum     -0.0002378396 -7.915954e-05 -0.0001656710 3.056640e-05  1.534364e-03 0.000000000
Bitcoin      -0.0001195707  3.282631e-06 -0.0001581579 6.628559e-05 -7.316185e-05 0.001098722
> ortho_doge
                  Cardano       Stellar  Binance.Coin      Litecoin      Ethereum       Bitcoin    Dogecoin
Cardano       2.944557e-03  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00 0.0000000000 0.000000000
Stellar       7.882955e-04  3.102283e-03  0.000000e+00  0.000000e+00  0.000000e+00 0.0000000000 0.000000000
Binance.Coin  1.405117e-04  3.295464e-04  2.747128e-03  0.000000e+00  0.000000e+00 0.0000000000 0.000000000
Litecoin     -4.062874e-05  1.577642e-04 -5.531385e-05  2.332057e-03  0.000000e+00 0.0000000000 0.000000000
Ethereum     -1.598007e-04 -1.295050e-04 -1.648295e-04  7.015462e-05  1.685505e-03 0.0000000000 0.000000000
Bitcoin      -9.612673e-05 -3.066337e-05 -4.515277e-05 -5.808547e-05 -9.731103e-05 0.0013312309 0.000000000
Dogecoin      5.546563e-04  3.789994e-04  2.314022e-04 -3.888928e-04 -3.044318e-04 0.0003316661 0.003907869
>
```

However, we note two interesting changes. First, in the five-minute dataset there are statistically significant non-zero impulse responses after the first time step consistent across all the cryptocurrencies. As an example, here is the graph of the response to Bitcoin from a shock from Bitcoin (below). There is a clear negative response to a positive shock from 20 to 50 minutes out.

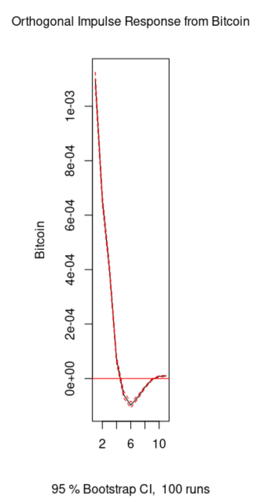

Figure 7: Bitcoin orthogonal IR, 5-minute

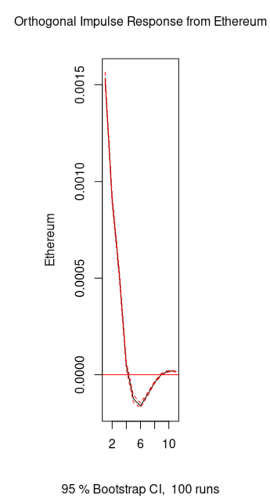

Figure 8: Ethereum orthogonal IR, 5-minute

Secondly, the responses onto itself were all considerably smaller. For example, the response of Cardano to a shock in Cardano was 33% smaller when looking at five-minute intervals.

4.2.2 Forecast Error Variance Decomposition (FEVD)

We also calculated the H-step-ahead generalized FEVD for each cryptocurrency, pre and post-Doge every five minutes (table of errors included in Appendix). We note three interesting observations. First, generally the smaller (in market cap) cryptocurrencies were more dependent on the larger cryptocurrencies. For example, 88% of the variance in Cardano's forecasts could be explained by a shock to Cardano itself, with 12% coming from the other five cryptocurrencies. However, 95% of the variance in Bitcoin's forecasts could be explained by a shock to Bitcoin itself.

Secondly, in general we see that every cryptocurrency saw their self FEVD percentage increase in the post-Doge dataset; e.g. the variance in a cryptocurrency's forecast contributed by a shock to that same cryptocurrency grew. For example, Cardano increased from 88% to 91%, Litecoin and Bitcoin from 95% to 98%, etc. We also note the substantial change in Binance Coin's decomposition. It went from 87% to 96%, by far the largest increase.

Lastly, we note that these percentages slightly decreased over time, demonstrating a larger dependency on other cryptocurrencies as time moves forward, across both pre-Doge and post-Doge. For example, at the first step forecast Bitcoin is at 95% and drops to 92% by the 10th-step forecast in the pre-Doge dataset. In the post-Doge dataset it drops from 98% to 97% by the 10th-step forecast.

4.3 Forecasting Methods

We also tried different model architectures to forecast target returns. These models were all applied to univariate time series for each currency. The following analysis was conducted on the Bitcoin time series.

We found that a simple VAR(3) model outperformed the more powerful non-linear univariate models in all of Mean Error (ME), Root Mean-Squared Error (RMSE), and Mean Absolute Error (MAE). We also found that out of all models, the Generalized Additive Autoregressive Model (AAR) with six penalized cubic splines performed the best. We see in the below example that the AAR model was able to better predict the increase in returns in the first two steps and decrease in returns at the 15th step.

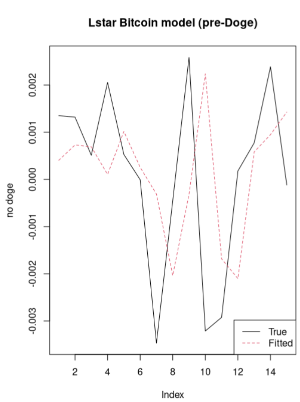

Figure 9: Lstar model

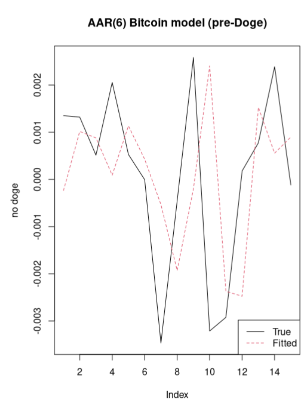

Figure 10: Additive Ar Model

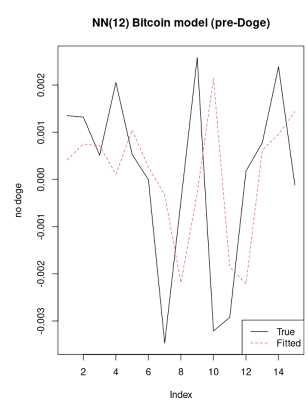

Figure 11: NN forecast

The table of the model test statistics are below.

	AR(3)	VAR(3)	Setar(1)	Setar(3)	Lstar(3)	Aar(3)	Aar(6)	NN(3)
ME	-2.95E-05	1.17E-05	-2.80E-05	-5.51E-05	-4.54E-05	-3.31E-05	-2.50E-05	-2.93E-05
RMSE	1.95E-03	5.70E-04	1.99E-03	1.96E-03	1.96E-03	1.96E-03	1.93E-03	1.95E-03
MAE	1.36E-03	3.46E-04	1.38E-03	1.36E-03	1.35E-03	1.35E-03	1.33E-03	1.36E-03

5 Conclusions

This study analyzes the results of non-linear modeling applied to cryptocurrency returns and quantifies network effects between the largest cryptocurrencies on the market. We show that there are many complex relationships between the several cryptocurrencies analyzed and that these can be utilized to better forecast individual currencies. Our simple VAR(3) model using all six cryptocurrencies performed the best out of the more powerful nonlinear, univariate models.

Furthermore, we provide evidence for a number of interesting conclusions about the relationships between cryptocurrencies. The orthogonal impulse responses showed larger instantaneous responses to shocks in smaller cryptocurrencies than larger. They also showed a consistent negative relationship between 20 to 50 minutes before settling to zero. Lastly the magnitude of the instantaneous orthogonal impulse responses were shown to be smaller in the post-Doge dataset, suggesting that the introduction of another cryptocurrency dampened the impact of a single shock to an individual cryptocurrency on itself.

The generalized FEVD showed a larger proportion of forecasting error could be explained by other cryptocurrencies in smaller cryptocurrencies. It also showed that this proportion slightly decreases with time, yet consistently remained high (over 90% across almost all cryptocurrencies) after all forecasts within 10 steps ahead.

6 Future Work

There are several aspects of the study that could be improved. For example, it is hard to conduct inference on the orthogonal impulse responses without knowing their dependency on the order, their distributional properties, and their repeatability. Is there a way to account for every possible ordering combination of the predictors to come to a general statistic conveying the information? What is the statistical significance of the computed values? And how much does our calculated values depend on the sample taken. If we were to compute these statistics on each half of the dataset, would they be strongly correlated?

There is also a lot more that could be done with the forecasting. A primary limitation was that all of the non-linear methods used could only be applied to univariate time series.

Finally, we did not explore using additionally features to improve forecasting performance, which would be very useful.

References

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7 Appendix

$Litecoin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.01612270	0.005621967	0.01602438	0.9525639	0.002592635	0.007074383
[2,]	0.01724565	0.004816927	0.01572011	0.9521605	0.002760488	0.007296371
[3,]	0.01716423	0.004607327	0.01544531	0.9521856	0.002762952	0.007834590
[4,]	0.01719132	0.004919020	0.01564820	0.9514696	0.002804339	0.007967547
[5,]	0.01750169	0.005320369	0.01619117	0.9502982	0.002784943	0.007903638
[6,]	0.01773228	0.005589267	0.01656188	0.9495179	0.002760114	0.007838597
[7,]	0.01779858	0.005644673	0.01662800	0.9493378	0.002752381	0.007838542
[8,]	0.01779963	0.005645643	0.01662527	0.9493206	0.002752277	0.007856585
[9,]	0.01780396	0.005650869	0.01664583	0.9492815	0.002753201	0.007864607
[10,]	0.01781152	0.005658498	0.01666771	0.9492438	0.002753643	0.007864839

$Ethereum

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.02196375	0.006587160	0.01838199	0.002584347	0.9495187	0.0009640568
[2,]	0.02419817	0.007113994	0.02092666	0.001992894	0.9435562	0.0022120966
[3,]	0.02594649	0.007670171	0.02101040	0.001845937	0.9407942	0.0027328171
[4,]	0.02609466	0.007731451	0.02100832	0.001942069	0.9402968	0.0029267492
[5,]	0.02608061	0.007703585	0.02111508	0.001958228	0.9402287	0.0029138249
[6,]	0.02625959	0.007708680	0.02120723	0.001943287	0.9399319	0.0029492714
[7,]	0.02640599	0.007725260	0.02124095	0.001951365	0.9396549	0.0030215107
[8,]	0.02644917	0.007734798	0.02123892	0.001964128	0.9395563	0.0030567152
[9,]	0.02644953	0.007735687	0.02123996	0.001968010	0.9395449	0.0030619633
[10,]	0.02645215	0.007734875	0.02124384	0.001967801	0.9395394	0.0030619231

$Bitcoin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.01090167	0.0004207234	0.02268597	0.007114049	0.0009725715	0.9579050
[2,]	0.01568310	0.0013219105	0.02661093	0.008217448	0.0012348627	0.9469318
[3,]	0.01797798	0.0024990977	0.02796042	0.009328653	0.0018820129	0.9403518
[4,]	0.01909599	0.0029107300	0.02813997	0.009777299	0.0020571440	0.9380189
[5,]	0.01915004	0.0029546748	0.02815036	0.009804592	0.0020695008	0.9378708
[6,]	0.01906669	0.0029564655	0.02832570	0.009772129	0.0020844435	0.9377946
[7,]	0.01911055	0.0030068744	0.02848401	0.009813509	0.0021335106	0.9374515
[8,]	0.01917596	0.0030541212	0.02853412	0.009864544	0.0021730064	0.9371982
[9,]	0.01920590	0.0030710849	0.02853594	0.009883534	0.0021838842	0.9371197
[10,]	0.01920938	0.0030731039	0.02853741	0.009884577	0.0021841434	0.9371114

$Cardano

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.8833825	0.04401279	0.02716550	0.01495176	0.02043392	0.010053549
[2,]	0.8757015	0.05192785	0.03183123	0.01390651	0.01804048	0.008592405
[3,]	0.8736766	0.05581987	0.03162616	0.01356821	0.01725551	0.008053693
[4,]	0.8722504	0.05735525	0.03160160	0.01352523	0.01717357	0.008093940
[5,]	0.8719593	0.05731244	0.03162645	0.01376639	0.01716461	0.008170838
[6,]	0.8720213	0.05704023	0.03161264	0.01396229	0.01711420	0.008249300
[7,]	0.8720685	0.05696443	0.03159035	0.01399955	0.01708280	0.008294346
[8,]	0.8720682	0.05697805	0.03157987	0.01399491	0.01707647	0.008302512
[9,]	0.8720495	0.05698856	0.03158027	0.01400285	0.01707609	0.008302741
[10,]	0.8720350	0.05698670	0.03158037	0.01401389	0.01707499	0.008309085

$Stellar

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.04442555	0.8916672	0.05206728	0.005262558	0.006185822	0.0003916309
[2,]	0.06353723	0.8566031	0.07034138	0.004011141	0.004958108	0.0005490787
[3,]	0.06785530	0.8500929	0.07326618	0.003866205	0.004286879	0.0006325224
[4,]	0.07048041	0.8466510	0.07411709	0.003784101	0.004350262	0.0006171338
[5,]	0.07082443	0.8459325	0.07396224	0.003855380	0.004553339	0.0008721277
[6,]	0.07076780	0.8452937	0.07403206	0.003980489	0.004629575	0.0012963322
[7,]	0.07073486	0.8448399	0.07417396	0.004019260	0.004631640	0.0016003415
[8,]	0.07073963	0.8446824	0.07422741	0.004022071	0.004631160	0.0016972937
[9,]	0.07074880	0.8446535	0.07423184	0.004022354	0.004638030	0.0017054586
[10,]	0.07075086	0.8446432	0.07422891	0.004026025	0.004643231	0.0017077246

$Binance.Coin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin
[1,]	0.02676365	0.05082046	0.8703149	0.01464076	0.01684866	0.02061158
[2,]	0.02901224	0.05689492	0.8661599	0.01376622	0.01533736	0.01882938
[3,]	0.02846162	0.05771006	0.8676730	0.01366549	0.01455396	0.01793585
[4,]	0.02846185	0.05846039	0.8668408	0.01364769	0.01467645	0.01791279
[5,]	0.02836198	0.05819871	0.8668913	0.01376093	0.01495747	0.01782959
[6,]	0.02819603	0.05781393	0.8673627	0.01385462	0.01506054	0.01771215
[7,]	0.02812821	0.05767722	0.8675921	0.01387353	0.01505325	0.01767572
[8,]	0.02812684	0.05766197	0.8676131	0.01387165	0.01504996	0.01767644
[9,]	0.02813176	0.05765956	0.8675968	0.01387468	0.01506078	0.01767645
[10,]	0.02812927	0.05765221	0.8675971	0.01387883	0.01506828	0.01767431

Figure 12: FEVD pre-Doge

$Litecoin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.0002969668	0.003673673	0.0002617476	0.9837318	0.001555833	0.001794535	0.008685484
[2,]	0.0002281195	0.006331087	0.0002353123	0.9795154	0.001540361	0.002317841	0.009831844
[3,]	0.0003684093	0.006925461	0.0004714839	0.9768655	0.001774520	0.002367047	0.011227628
[4,]	0.0003720996	0.007876325	0.0005158456	0.9738151	0.002281050	0.002469234	0.012670385
[5,]	0.0003854940	0.007972876	0.0005219664	0.9727703	0.002602345	0.002540386	0.013206658
[6,]	0.0004675096	0.007917033	0.0006515912	0.9725482	0.002658756	0.002579745	0.013177128
[7,]	0.0005025309	0.007905928	0.0007656375	0.9723259	0.002651949	0.002709926	0.013138088
[8,]	0.0005080587	0.007942901	0.0008010793	0.9719734	0.002708538	0.002831311	0.013234741
[9,]	0.0005105687	0.007984800	0.0008008298	0.9717419	0.002772357	0.002841818	0.013347717
[10,]	0.0005199463	0.007997203	0.0008130241	0.9716407	0.002792210	0.002846883	0.013390048

$Ethereum

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.008371105	0.008910764	0.01145782	0.001511468	0.9556799	0.003642653	0.01042631
[2,]	0.007972063	0.011192858	0.01454172	0.001139445	0.9448636	0.004169767	0.01612052
[3,]	0.007568689	0.012172923	0.01714080	0.001405524	0.9368093	0.007861089	0.01704164
[4,]	0.007550232	0.012241280	0.01756987	0.001402453	0.9349165	0.008695916	0.01762380
[5,]	0.007480018	0.012177781	0.01740720	0.001398616	0.9354155	0.008658402	0.01746247
[6,]	0.007420192	0.012227662	0.01747472	0.001495100	0.9352621	0.008805910	0.01731427
[7,]	0.007412784	0.012269963	0.01763612	0.001555048	0.9346915	0.009125994	0.01730862
[8,]	0.007413042	0.012274414	0.01771110	0.001573126	0.9344117	0.009295607	0.01732101
[9,]	0.007412143	0.012273951	0.01771190	0.001573080	0.9343920	0.009311984	0.01732494
[10,]	0.007414705	0.012278232	0.01771126	0.001580720	0.9343792	0.009313946	0.01732192

$Bitcoin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.005040696	0.001555121	0.001549535	0.001788476	0.003736915	0.9804103	0.005918934
[2,]	0.004877656	0.002101910	0.001230811	0.004604631	0.003013851	0.9793549	0.004816196
[3,]	0.004796200	0.005192171	0.001610917	0.004182938	0.002779793	0.9766581	0.004779854
[4,]	0.004847977	0.005685647	0.002018132	0.004247366	0.002906837	0.9747080	0.005586018
[5,]	0.004962500	0.005683593	0.002451107	0.004871059	0.002907367	0.9735785	0.005545914
[6,]	0.005069858	0.005927262	0.002547641	0.004909491	0.002939473	0.9730007	0.005605597
[7,]	0.005078441	0.006274464	0.002539355	0.004897562	0.002995458	0.9722501	0.005964615
[8,]	0.005073920	0.006525970	0.002565313	0.004930077	0.002998239	0.9717452	0.006161272
[9,]	0.005079298	0.006555346	0.002622756	0.004967927	0.003001001	0.9715813	0.006192399
[10,]	0.005084841	0.006554524	0.002659578	0.004988382	0.003014460	0.9715029	0.006195297

$Dogecoin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.01788713	0.01476466	0.005326516	0.008280367	0.01023176	0.005661974	0.9378476
[2,]	0.01959477	0.02074372	0.013778913	0.006786492	0.01153318	0.007096794	0.9204661
[3,]	0.01942718	0.02094594	0.014820770	0.006015650	0.01038052	0.016126424	0.9122835
[4,]	0.01938272	0.02140785	0.016537296	0.006134373	0.01052138	0.019969091	0.9060473
[5,]	0.01929635	0.02127181	0.016564613	0.006504781	0.01117141	0.021360625	0.9038304
[6,]	0.01920338	0.02108950	0.016398465	0.006564913	0.01136059	0.021174376	0.9042088
[7,]	0.01915668	0.02102862	0.016423513	0.006552752	0.01131919	0.021538328	0.9039809
[8,]	0.01913105	0.02099739	0.016501614	0.006546237	0.01132203	0.022273204	0.9032285
[9,]	0.01912306	0.02098900	0.016555067	0.006560576	0.01137592	0.022568555	0.9028278
[10,]	0.01911822	0.02098381	0.016558647	0.006577055	0.01140466	0.022602513	0.9027551

$Cardano

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.9119934	0.05531384	0.002346037	0.0002753106	0.007988441	0.004688936	0.01739402
[2,]	0.9025503	0.05636277	0.004216143	0.0007657372	0.008876905	0.005995711	0.02123241
[3,]	0.8967347	0.05752434	0.004635298	0.0007601675	0.008797675	0.006758979	0.02478882
[4,]	0.8937773	0.05786861	0.005612264	0.0009928850	0.008788283	0.006772695	0.02618800
[5,]	0.8933769	0.05747927	0.005960282	0.0010201874	0.009085315	0.006880155	0.02619788
[6,]	0.8933189	0.05706377	0.006074403	0.0010243017	0.009348504	0.007162479	0.02600767
[7,]	0.8930674	0.05696276	0.006056066	0.0010208506	0.009422647	0.007338239	0.02613206
[8,]	0.8927999	0.05698007	0.006069163	0.0010217532	0.009418635	0.007364652	0.02634581
[9,]	0.8926453	0.05698224	0.006117615	0.0010239504	0.009431917	0.007364862	0.02643413
[10,]	0.8925777	0.05696851	0.006149896	0.0010248274	0.009455417	0.007384383	0.02643931

$Stellar

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.05477098	0.9030429	0.01474469	0.003372347	0.008419976	0.001432401	0.01421673
[2,]	0.06184172	0.8784947	0.01906578	0.006917405	0.006560018	0.001668642	0.02545175
[3,]	0.06288854	0.8711510	0.02028649	0.007199959	0.006130216	0.002220653	0.03012316
[4,]	0.06301005	0.8684719	0.02153026	0.007684986	0.006122655	0.002240465	0.03093965
[5,]	0.06300049	0.8682637	0.02165966	0.007660872	0.006133696	0.002261166	0.03102046
[6,]	0.06310034	0.8673558	0.02147036	0.007592919	0.006106742	0.002380455	0.03199337
[7,]	0.06319884	0.8663445	0.02139034	0.007594741	0.006079280	0.002438434	0.03295383
[8,]	0.06321435	0.8659333	0.02143399	0.007609877	0.006072499	0.002443319	0.03329269
[9,]	0.06320843	0.8658451	0.02149950	0.007619089	0.006075181	0.002447158	0.03330555
[10,]	0.06320849	0.8657807	0.02152394	0.007618447	0.006076767	0.002459234	0.03333245

$Binance.Coin

	Cardano	Stellar	Binance.Coin	Litecoin	Ethereum	Bitcoin	Dogecoin
[1,]	0.002477262	0.01572375	0.9630057	0.0002562329	0.01154565	0.001522027	0.005469402
[2,]	0.003729103	0.02013323	0.9483307	0.0002857545	0.01085136	0.001541290	0.015128604
[3,]	0.004332946	0.02174080	0.9469250	0.0002598730	0.01046964	0.002458175	0.013813612
[4,]	0.004639756	0.02229185	0.9451949	0.0009099799	0.01047629	0.002494813	0.013992396
[5,]	0.004680657	0.02228102	0.9447403	0.0012401128	0.01044252	0.002531562	0.014083818
[6,]	0.004647631	0.02215044	0.9445915	0.0015510246	0.01036612	0.002714815	0.013978487
[7,]	0.004653746	0.02213107	0.9446047	0.0015650600	0.01033876	0.002762379	0.013944278
[8,]	0.004677658	0.02217087	0.9444612	0.0015649198	0.01033810	0.002852597	0.013934621
[9,]	0.004687331	0.02218422	0.9443935	0.0016007042	0.01034443	0.002855763	0.013934078
[10,]	0.004688316	0.02218529	0.9443675	0.0016238724	0.01034629	0.002855816	0.013932885

Figure 13: FEVD post-Doge