Cryptocurrency Time Series Analysis

DSC 425 Time Series Analysis and Forecasting

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Non-Technical Summary

Cryptocurrencies are a dynamic, rapidly evolving market. The most prevalent currency in the market, Bitcoin, has grown in value from $327 in 2015 to $65,000 in 2021. This exponential growth has led to many different speculations on how cryptocurrencies could be explained or modeled. We focused on Bitcoin, the most prevalent and widely accepted coin. We explored multiple avenues for describing relationships between Bitcoin and other financial instruments.

We began by analyzing the daily closing values of Bitcoin and then we investigated how it could relate to the daily closing values of the traditional stock market, as well as with crypto-mining stocks and other cryptocurrencies. We modeled Bitcoin on its own, as well as in models with the S&P 500 index, Ethereum, Chainlink, Nvidia (NVDA), and Advanced Micro Devices (AMD).

We found that Bitcoin is more volatile than the traditional stocks in the dataset. There was no statistically relevant relationship between Bitcoin and the S&P 500 or the graphics card manufacturer stocks. However, there are relationships with Bitcoin and smaller cryptocurrencies like Ethereum and Chainlink that could potentially be further exploited in a higher-frequency model. There was also a distinct shift in behavior over the last year. We believe that a model focused on the prior year alone, or a higher frequency intra-day model, may potentially have better performance.

Overall, we found that there were no exploitable relationships between bitcoin, the stock market, and crypto-mining stocks. The most applicable model was only capable of forecasting the mean of the series instead of being able to capture the true variance. In order to truly benefit there would need to be significant lag correlation between the series.

For future work, we believe that higher frequency data may have more utility. Our analysis was limited to daily values which appeared to only have spurious correlation. There might be a chance to find some significant correlation if analyzing a more granular series such as hourly intervals or by minute intervals.

Punch list items have been addressed and are highlighted in the body of the report.

Technical Summary

Exploratory Analysis

Our dataset consists of 6 series pulled from Yahoo Finance: Bitcoin, Ethereum, Chainlink, AMD, NVDA, and the S&P 500. We examined adjusted price data on each series, from October 1, 2016 to September 30, 2021. Because Chainlink was created more recently, the series started on October 1, 2017.

The dataset was clean, so little pre-processing was required. However, the discrepancy between cryptocurrency and market trading hours meant there were mismatching series. Cryptocurrencies are traded at all hours, including weekends and holidays. Accordingly, when we analyzed any cryptocurrency with a traditional stock pair, we opted to drop non-regular trading days so that the frequencies matched.

We began the exploratory analysis of each series by examining their overall distribution, as well as their behavior in a time plot. This allowed us to determine whether there was multiplicative or additive behavior, whether the series was stationary, and what transformations were necessary.

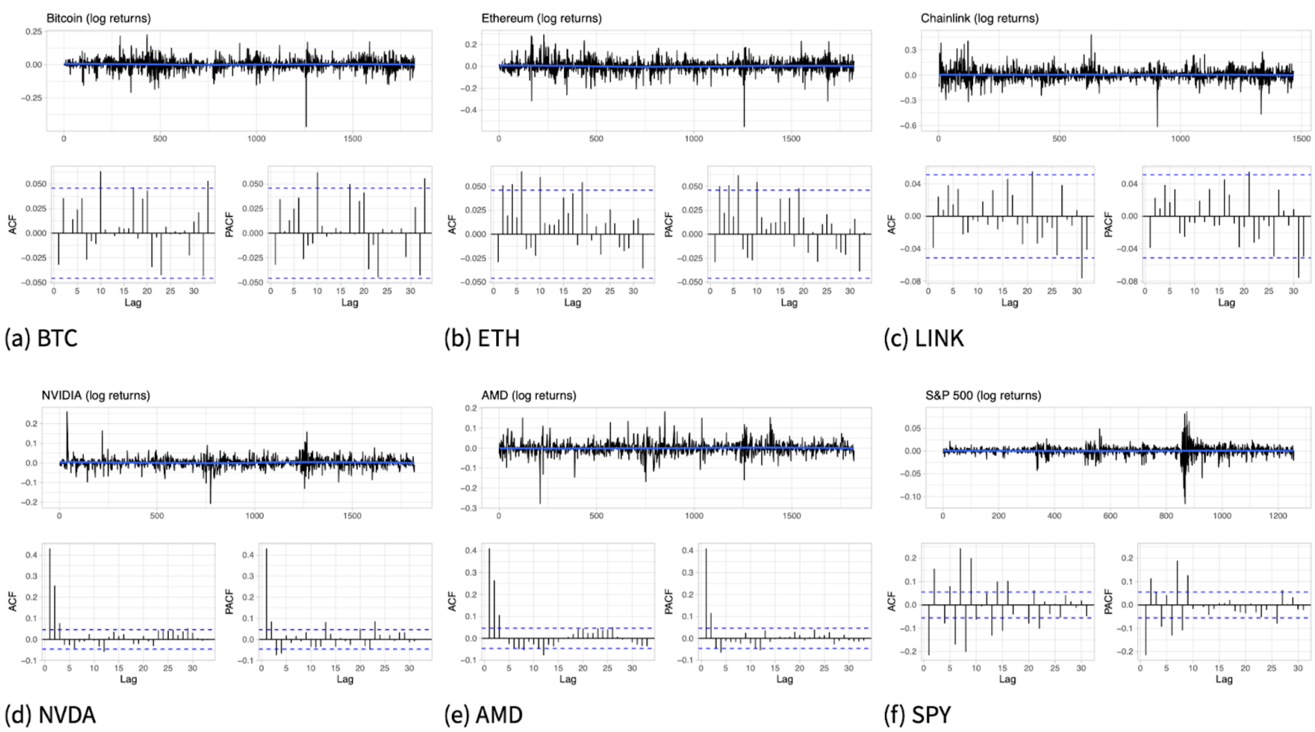


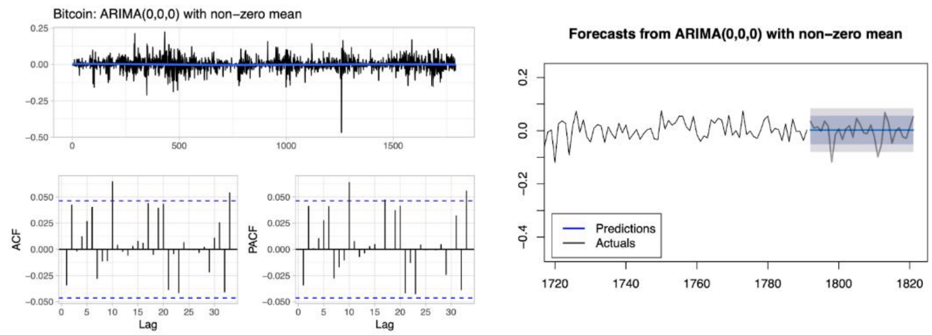
Figure 1 Log returns, ACF, and PACF of the Time Series Analyzed.

To confirm weak stationarity, we conducted Augmented Dickey-Fuller and KPSS Tests on each series. If the series was not stationary, a log transformation and/or differencing was applied. In most of the series, we found that taking a log return was necessary in order to achieve weak stationarity.

Finally, we explored each series for serial correlation. Using ACF and PACF plots of each series aided in determining which order would be appropriate for ARMA models.

Analysis of Time Series

Bitcoin



(a) Residuals (b) Forecast

Figure 2 BTC Auto Arima Model

Model fitting: We began by exploring whether a time regression or constant would be necessary. To determine whether a unit root was present, we applied Dickey-Fuller tests to both the log transformed and log return values of the series. The log transformed series was not stationary, even with a trend or constant applied. The log returns, however, were stationary even without a constant or a time trend. We concluded that a time regression would not be necessary for the analysis, and moved forward with ARMA modeling on the log returns.

The autocorrelation plots did not display straight-forward moving average or autoregressive behavior. We then looked at the EACF to inform us more on potential orders for our ARMA model. Based on the EACF, we found that an ARIMA(0,0,0) would be the best prospect. Still wanting to explore other possibilities, we experimented with a few simple auto regressive and moving average models.

For the Bitcoin log return series, we fit the following models:

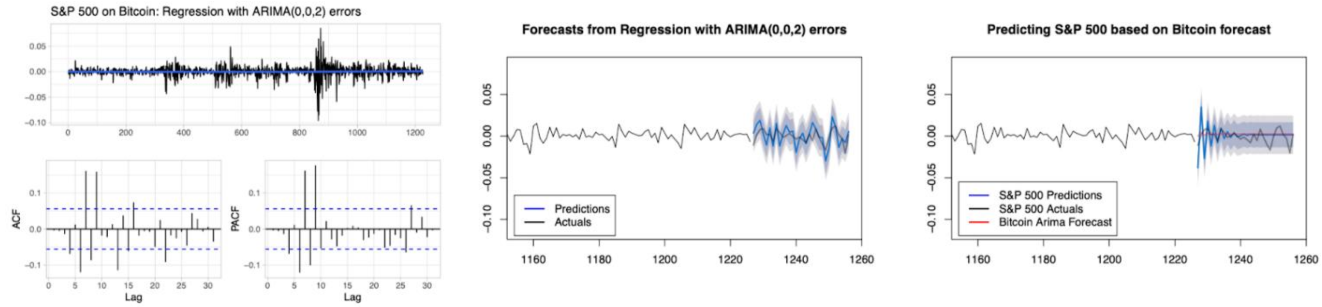
- ARMA (1,0)
- ARMA(0,1)
- ARMA(1,1)
- ARIMA(0,0,0)
- and an ARIMA(0,0,0) with Drift

The ARIMA(0,0,0) model had the lowest AIC/BIC and standard error.

Residual Analysis: The residuals did not show any evidence of ARMA behavior and appeared to be white noise. This was further confirmed by the Ljung-Box test achieving p-values that failed to reject white noise.

Forecast Analysis: The best model for Bitcoin was an ARIMA(0,0,0). Since Bitcoin is best modeled as a random walk, the forecast values were simply the mean of the series.

Bitcoin and S&P 500



(a) Residuals (b) Forecast (c) Forecast using Bitcoin predictions

Figure 3 Bitcoin and S&P 500 forecasts

Model fitting: Modeling the S&P 500 by regressing on Bitcoin, knowing that the correlation is already weak, we could not find a reasonable model. But Auto Arima suggested an ARMA(0,2) model by regressing on Bitcoin.

Residual Analysis: The residual analysis showed that the model captured all the auto-correlations. This was also validated statistically using the Ljung-Box test, where it could not reject the series independence at a p-value of .96. So, the residuals are similar to white noise, and there are no further auto-correlations to be captured.

Forecast Analysis: The 30 days predictions seem to capture the significant movements, but it was generally spurious and not reliable. And the residuals seem to have sort of seasonality at lag 9. **To address the punch list**, we added a more zoomed in view of the SP500 predictions to better demonstrate the spurious nature. Also, we added a forecast plot based on the predicted values of bitcoin. Although, it's worth mentioning the bitcoin model is ARMA(1,1) with non-zero mean; a weak model. Still, we added the forecast out of curiosity to implement the punch list suggested approach.

Using only the past year time-span; some S&P 500 and Bitcoin patterns seem to have developed and show interesting correlations. In future work, we might try to investigate this further.

Bitcoin and Crypto Mining Stocks

One route of investigation went towards examining the potential relationship between cryptocurrencies and graphic card manufacturers. We focused on NVIDIA and AMD. These companies manufacture GPUs that are heavily used for mining cryptocurrencies. In both of the models, we worked with the log returns, which had weak stationarity.

Model fitting: We proceeded by examining the lagged cross correlations between each series and the Bitcoin log returns. The cross correlations between Bitcoin and Nvidia values at varying lags are shown below.

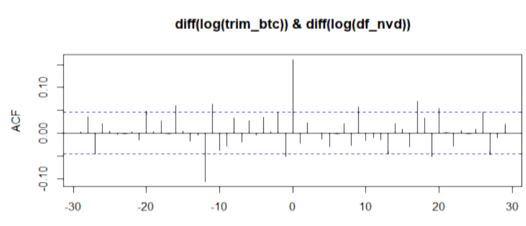


Figure 4 Cross correlation plot of BTC & NVDA log returns

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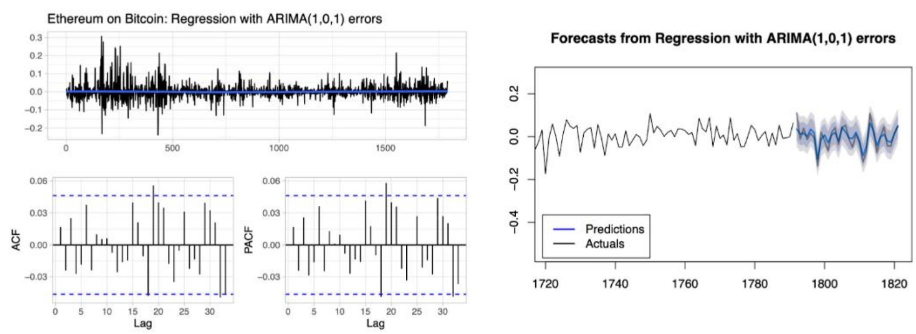
Most of the cross correlation values were within the confusion boundaries. There was a small degree of cross correlation at lag-1 for AMD and lag-12 for NVIDIA. The cross correlations were minor so we suspected that they may be spurious, but decided to explore them regardless. After determining the lag order, we regressed Bitcoin on AMD and NVIDIA with lag-1 and lag-12, respectively.

Residual Analysis: The residuals of the fitted models had autocorrelation and were consistent with white noise in the Ljung Box test. However, the cross correlation models underperformed relative to the base ARIMA(0,0,0) model.

Forecast Analysis: All the models yielded insignificant coefficients. We decided not to form forecasts with the NVDA and AMD focused models.The Bitcoin regression with an AMD lag-1 coefficient had a standard error of 0.04, as opposed to 0.002 in the original model. The AIC and BIC underperformed as well, relative to the Bitcoin ARIMA (0,0,0) model. Which ultimately confirms that any serial correlation in or between the log returns of the series is spurious and there is no auto-correlation to exploit and the best we can do is forecast the mean.

Bitcoin and Ethereum



(a) Residuals (b) Forecast

Figure 5 Bitcoin/Ethereum Forecast and Residuals

Model fitting: Modeling Etherium by regressing on Bitcoin showed a high correlation with a regression ARMA (1,1) model.

Residual Analysis: The residual analysis showed that the model captured all the auto-correlations. This was also validated statistically using the Ljung-Box test, where it could not reject the series independence at a p-value of .46. So, the residuals are similar to white noise, and there are no further auto-correlations to be captured.

Forecast Analysis: The 30 days predictions captured most of the test data movements, and the forecast projections are very close to the actuals. We acknowledge that this is a prediction at lag-0 which is meaningless, but again the Bitcoin model is weak anyway to predict based on its forecast. (We proved the approach only for the S&P 500)

Bitcoin and Chainlink

Chainlink is a newer but popular cryptocurrency with a market capitalization of only about 1% of Bitcoin's and a trading volume of about 3% of Bitcoin's. Our theory was that the performance of Chainlink's log returns depends heavily on the performance of Bitcoin's log returns. After analyzing each cryptocurrency individually, we ran a time series regression to see how much Chainlink's log returns depend on Bitcoin's log returns. Only four years of data were available for Chainlink, so we analyzed a shorter time frame.

Model Fitting: The two series were each split into train and test subsets. The train subset of Bitcoin was used as the xreg, or independent variable. The train subset of Chainlink was used as the dependent variable. An ARIMA(0,0,0) model and an ARIMA(1,0,0) model that was selected by auto.arima were tested. The coef test showed that the coefficient for the regression term was a very strong 93%.

Residual Analysis: The plot of residuals and the ACF and PACF for the residuals were examined for autocorrelations and the Ljung-Box Test was used to determine if the residuals were white noise. A backtest was performed using the train subsets to select the model with the lowest Mean Absolute Percentage Error.

Forecast Analysis: The ARIMA(0,0,0) model was the best fit model given it's lower MAPE, significant regression term and white noise residuals. **Punch list item:** This model was used with the test subsets of each series to create the forecast from the regression of Bitcoin on Chainlink. The actual Chainlink log returns were added to compare with the forecast. The result was that the forecast log returns were pretty close to the actual log returns.

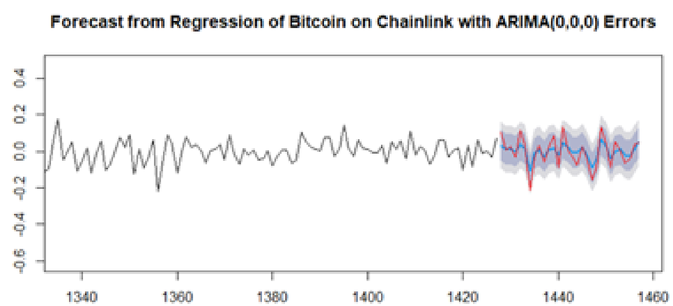


Figure 6 Bitcoin/Chainlink model forecast

Garch Analysis **(Punch list item)**

Investigating Garch Effects (Bitcoin)

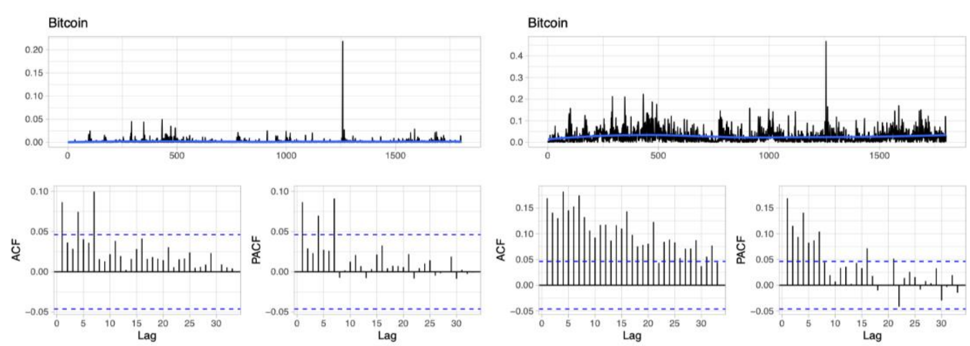
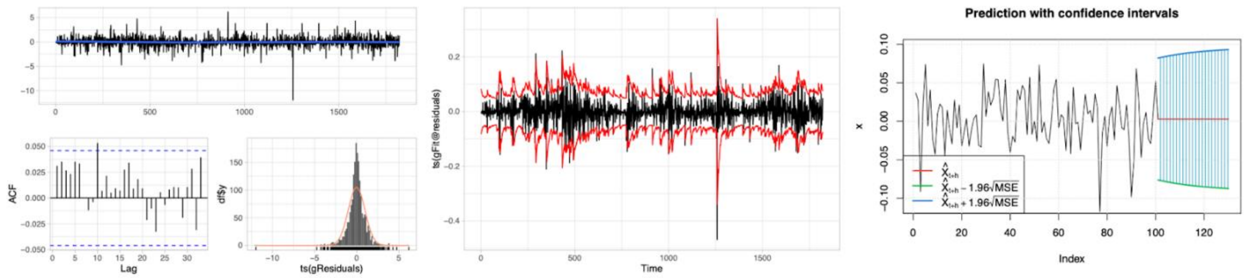


Figure 7

- Using Bitcoin Arima model: ARIMA(0,0,0) with non-zero mean. Testing the squared residuals for auto-correlations, Ljung-Box test accepted the existence of auto-correlations at p-value 0. Testing the absolute residuals for auto-correlations, Ljung-Box test accepted the existence of auto-correlations at p-value 0.

Garch Modeling (Bitcoin)

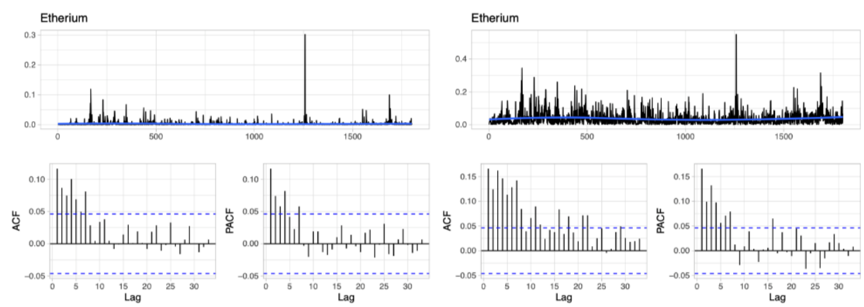


(a) Residuals (b) Variance (c) Forecast

Figure 8 Bitcoin Garch model

- formula = arma(0,0) + garch(1,1)
- Testing series for auto-correlations, Ljung-Box test cannot reject time series independence at p-value 0.18. The series is whitenoise and there are no auto-correlations. Testing series for normality, Jarque-Bera test accepts non-normal distribution at p-value 0 (Skewness: -0.94 Kurtosis: 14.08)

Investigating Garch Effects (Ethereum)

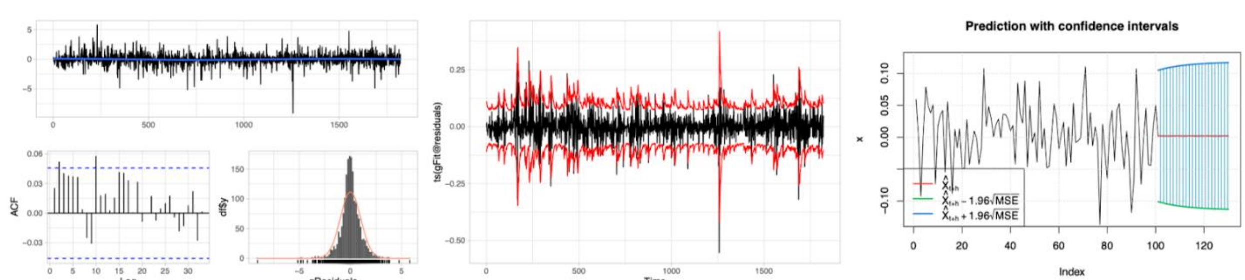


(a) Squared Residuals (b) Absolute Residuals

Figure 9 Ethereum Garch Model

- Using Ethereum Arima Model: ARMA(1,0,2) with non-zero mean Testing the squared residuals for auto-correlations, Ljung-Box test accepted the existence of auto-correlations at p-value 0. Testing the absolute residuals for auto-correlations, Ljung-Box test accepted the existence of auto-correlations at p-value 0.

Garch Modeling (Etherium)



(a) Residuals (b) Variance (c) Forecast

Figure 10 Ethereum Garch model

- formula = arma(0,0) + garch(1,1)
- Testing series for auto-correlations, Ljung-Box test cannot reject time series independence at p-value 0.28. The series is whitenoise and there are no auto-correlations. Testing series for normality, Jarque-Bera test accepts non-normal distribution at p-value 0 (Skewness: -0.5 Kurtosis: 6.85)

Garch Analysis (Chainlink)

Model Fitting: The ARIMA(2,0,2) model selected by auto.arima was used for GARCH analysis. The coeftest showed that both AR and both MA terms were significant.

Residual Analysis: A plot and ACF were performed for both the residuals squared and the absolute value of the residuals from the ARIMA model. It was decided to get the parameters for the model from the residuals squared. An ARCH(1) model was tried first. Next, a secondary residual analysis was done on the model of the residuals. There were still autocorrelations in the plot and ACF of the residuals. At order 3, all coefficients were significant and the residuals appeared to be white noise. The Box-Ljung Test confirmed white noise residuals. After the ARCH modeling, we tried a GARCH(1,1). All coefficients were significant and both the residuals and residuals squared were white noise. The skewness was -0.57 and the kurtosis was 8.97. Last, garchFit was used to combine the ARIMA(2,0,2) with GARCH(1,1). Both AR and both MA terms were significant. After standardizing the residuals to get the GARCH residuals, the Jarque -Bera Test rejected the data coming from a normal distribution. The residuals were plotted with the estimated volatility plotted over them.

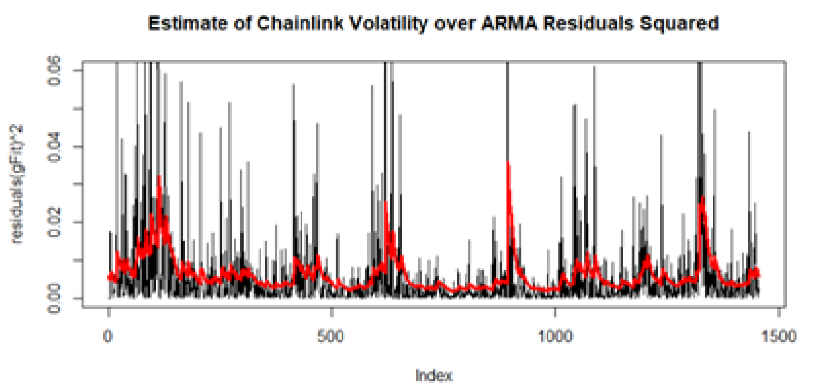


Figure 11 Estimated Chainlink volatility

Forecast Analysis: Finally, a prediction was run for 1 step ahead with a resulting forecast of 0.003.

Comparison of GARCH results for three cryptocurrencies:

	Skewness	Kurtosis
Bitcoin	-0.94	14.08
Ethereum	-0.5	6.85
Chainlink	-0.57	8.97

Figure 12

While all 3 cryptocurrencies are moderately negatively skewed, Bitcoin is the most skewed by a good margin. All 3 cryptos have kurtosis greater than a normal distribution, but again, Bitcoin is considerably higher than the others.

Vector Autoregression **(Punch list item)**

In VARselect, we examined potential models with an order of 1-20. A maximum order of 1 or 2 yielded the best results in all of the metrics provided. We experimented with both, along with a handful of higher order models, and found that the 2nd order model was better. The p-value in the Portmanteau test was 0.01, rejecting no autocorrelation with a high degree of confidence. Unfortunately, all of the models failed the test because the residuals had autocorrelation.

We proceeded with modeling the forecasts of the 2nd order model, using the last 10% of the Bitcoin series as a hold-out set. It did not follow the behavior of the hold-out set and quickly flatlines to the mean.

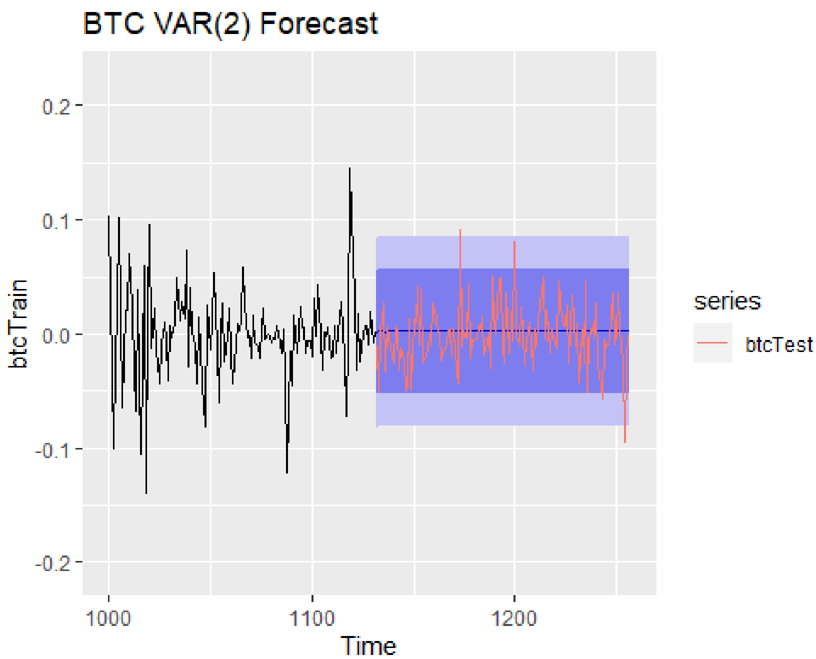


Figure 13 Vector Autoregression forecast for Bitcoin

Analysis of Results and Discussion

- The best ARIMA model for Bitcoin was in the order of (0,0,0) without drift. It had little predictive value, given that the forecast was simply the mean of the series.
- Ethereum is less spurious than Bitcoin and shows some auto-correlations that could be exploited.
- There is a significant correlation between Ethereum and Bitcoin at lag 0, so this relation might need to be investigated at a higher intra-day frequency to find a lag to exploit future predictions.
- For NVDA and AMD, we found small degrees of autocorrelation, but the lagged cross correlation models underperformed relative to the base ARIMA(0,0,0) model when predicting Bitcoin.
- The best fit model when regressing Bitcoin on Chainlink was an ARIMA(0,0,0), which is just a random walk. While no predictive value for daily prices, the coefficient for the regression term was a very strong 93%, indicating that Chainlink's performance is greatly impacted by Bitcoin's performance.
- The traditional stock market represented by the S&P 500 and the Crypto market represented by Bitcoin were not correlated over the past 5 years, but this seems to have changed during the past year and needs another investigation to focus only on the past year.
- We believe that a more granular analysis of the data may produce more utility than a daily approach. Observing each series by the minute or hour on a shorter-term basis may result in more interesting findings. We also noticed that there was a distinct shift in behavior in the stock market in the last couple of years, largely from the COVID pandemic.

Appendices

The following appendices will be submitted as separate files.

You can also click the links to access them :

- DSC425_Final_Project_Group4_Data.csv (datafile for all series)
- Appendix_MouradA.pdf
- Appendix_GerardoP.pdf
- Appendix_JosephP.pdf
- Appendix_EvelinaR.pdf