A study and backtest of correlation moving average and its implications for creating a profitable trading algorithm.

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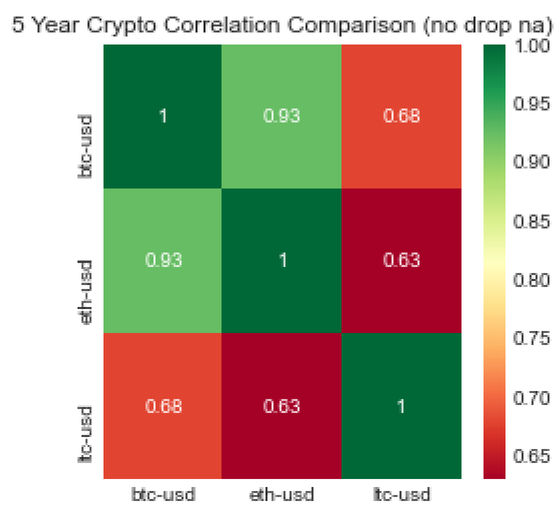
This study was motivated by the noticeably large correlation effect in cryptocurrency markets. [fig. 1]. Our goal was to understand this situation and identify its potential utilization for a profitable trading algorithm. We were also interested in working with an unconventional idea and innovating something new. Basic research yielded numerous insights and drawbacks to strictly correlation-based trading. Mean reversion was a highlighted concept throughout many sources which suggests a strong correlation is not one-to-one with a strong chance of reverting to a mean price–there may be unknown variance at play [1,2]. Another was the idea that observable correlations between any two stocks may not resolve to valid inter-stock dependencies but rather



to the adhesive effect between those assets and a larger index [3]. We attempted to diagnose these thoughts through our hypotheses below:

1. **Development of CORRMA: Correlation Moving Average Indicator.**
    - Determine if trading on a pair based on the indicator outperforms buying and holding *either* asset in the pair (crypto, stocks, sectors).
2. **Applied the SARIMA statistical model to the crypto time series.**
    - Transparent statistical regression model to fit and predict price.

CORRMA

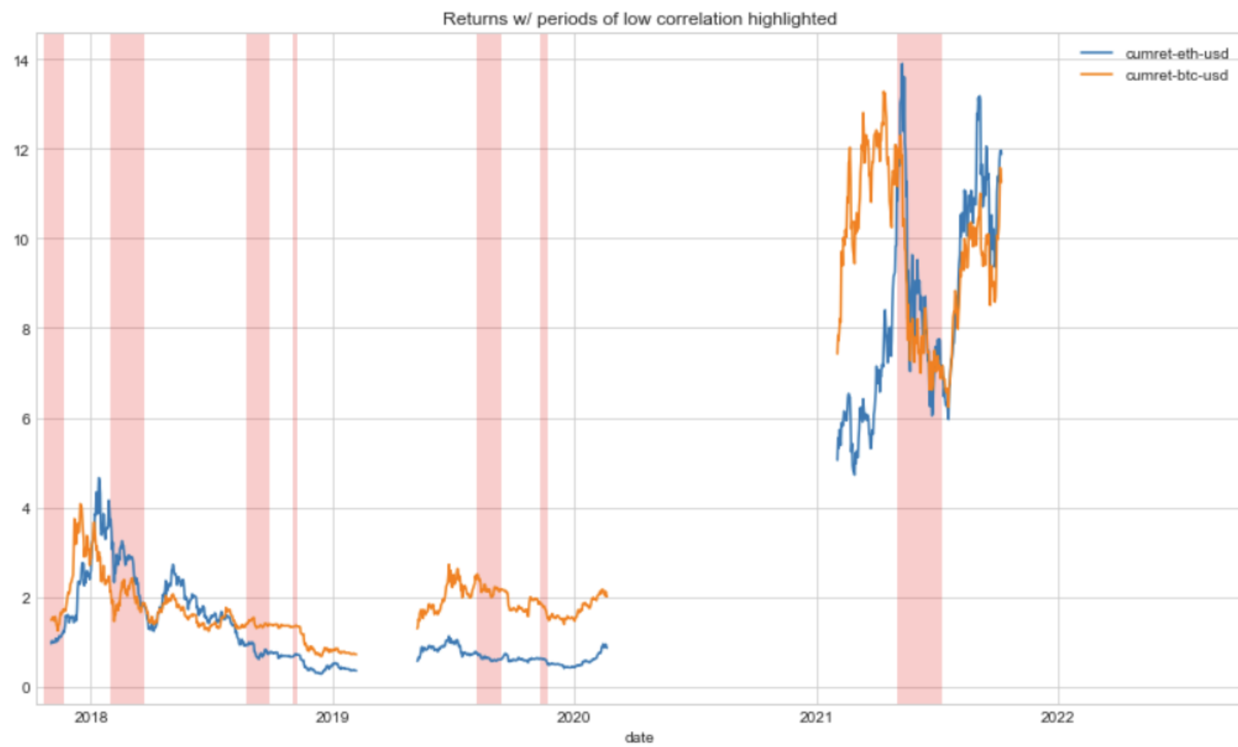
The CORRMA indicator is an extension of broad correlation calculations to a moving average which aids in tracking trends based on a rolling data window over an asset's timeframe. The initial trading algorithm relied on daily price data and two parameters:

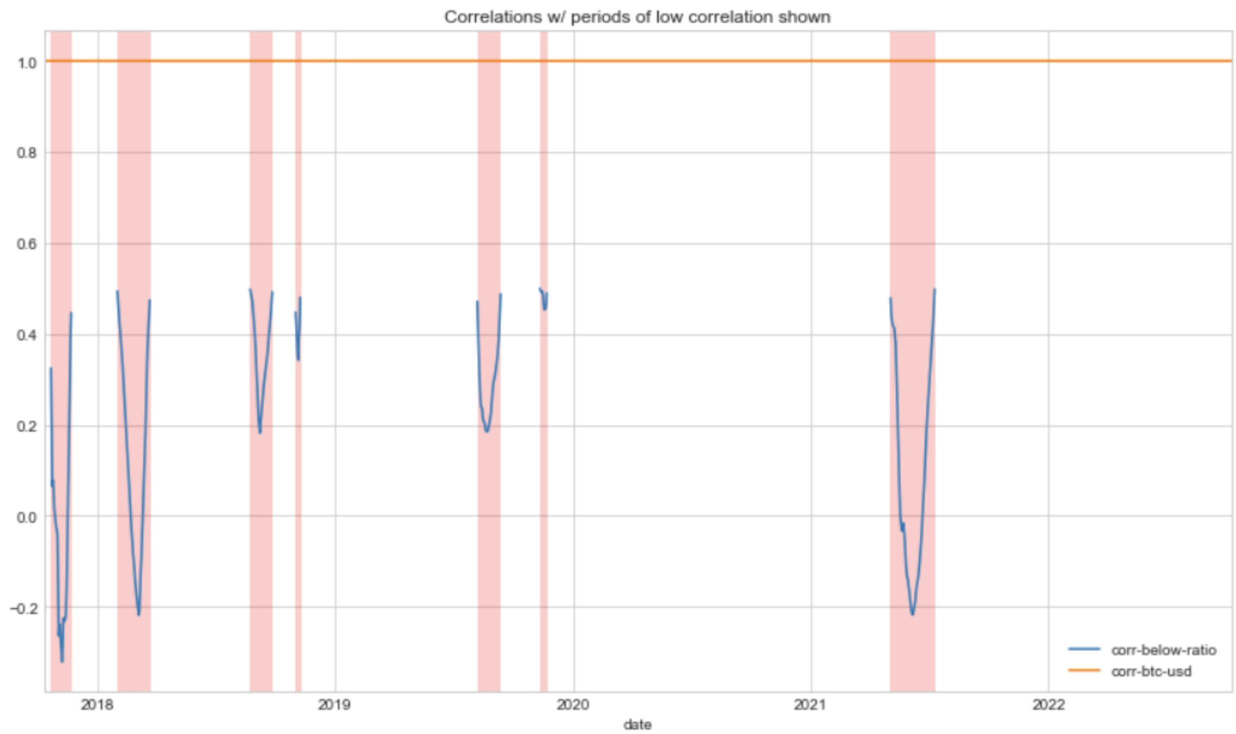
- *WINDOW* = rolling timeframe for correlation computations.
- *THRESHOLD* = correlation threshold to trigger an action.

Each day:

1. Compute past CORRMA using *WINDOW* days.
2. If correlation is <= *THRESHOLD*, swap from the original asset to the other.
3. If correlation > *THRESHOLD*, swap back to the original asset.

Our initial analysis was to determine moments of lower correlation between highly correlated assets such that these moments would present a trading signal. We first created a Jupyter notebook to find periods of low correlation based on *window* and *threshold* inputs. The red regions below are where the correlation falls below the *threshold,* and our algorithm should make a trade (BTC vs. ETH). This graph highlights CORRMA(90 day, 0.3)





Next, we implemented the algorithm on QuantConnect for backtesting and analysis. ***(Codebase attached below).*** Through numerous backtests and optimizations, we came to various conclusions regarding CORRMA's usability as a basic technical indicator.

Cryptocurrencies

Bitcoin is the largest cap asset in the crypto market and carries a large correlation between it and the other top-10 coins, one of which is Ethereum. We thoroughly studied the pairing to determine if our algorithm was successful ***(see technical appendix for details)***. It started with buying BTC, waiting for the indicator to initialize, and then swapping to ETH when the threshold is triggered. Our process started with testing our novel approach and then iteratively generating new hypotheses by understanding the Sharpe ratio, average win/loss rates, and other trends we noticed through the data.

1-1-1 - Novel analysis → **failed**

1-1-2 - Compete divergence CORRMA → **failed**

1-1-3 - Changing time frame → **small breakthrough**

1-1-4 - Swapping the original asset → **major breakthrough**

1-1-5 - Adjusting the algorithm trading criteria → **no change**

1-1-6 - QuantConnect Optimizations → **success**

1-1-7 - Comparing results with other cryptocurrency pairs → **success**

1-1-8 - In-sample vs. out-of-sample testing → **failed, needs more analysis**

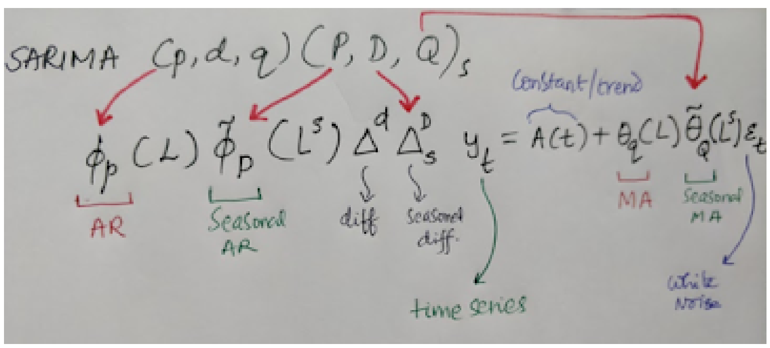
Our conclusions indicate that an in-sample backtest/optimization for an ETH v. BTC algorithm improves upon a 5-year B&H strategy by 3.75x, which, when applied to LTC v. BTC and ZEC v. BTC pairings, also netted 1.15x and 1.6x returns respectively. However, out-of-sample prediction does not give the same results and leaves room for future development.

Stocks v. ETFs v. Large Market

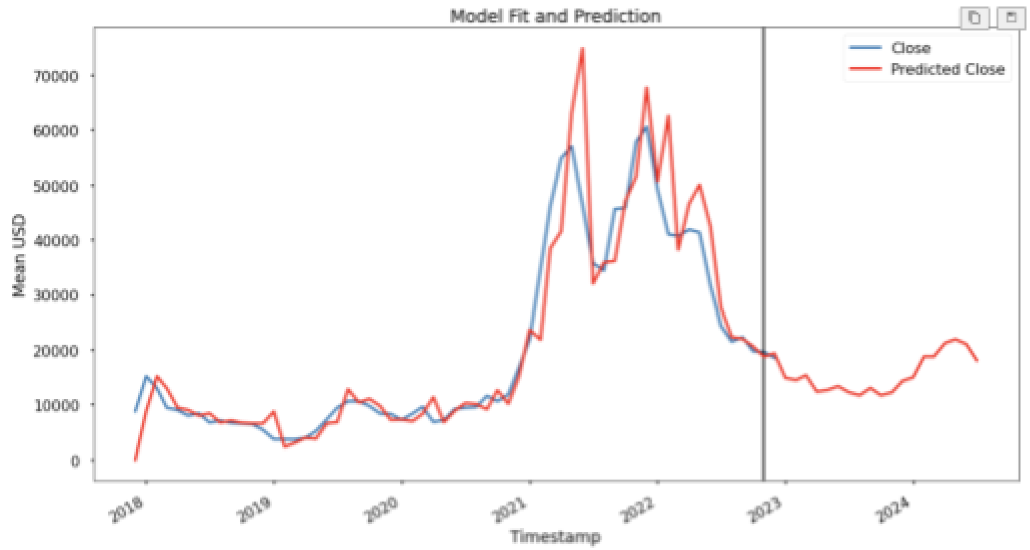
We started by comparing stock-to-stock in the same market and sector-to-sector. After reviewing academic reports from peers, the idea shifted towards comparing individual stocks to their sectors as a whole. We also compared individual sectors to the larger market. This evolved into the final version where we picked a single stock Amazon vs. its sector market XLY. For sectors to larger markets, we used XLK vs. SPY. We created B&H benchmarks for Amazon, XLY, XLK, and SPY and tested CORRMA against the benchmarks to see if we outperformed. After testing different variations against the benchmark, we found that a window of 90 days and a high to medium CORRMA threshold gave the best results for stocks-to-sectors. For sectors-to-larger markets, it was found that a window of 150 and a high threshold worked the best. These optimal variables were then tested against different periods to see if they stayed consistent.

ARIMA

We acquired small-cap crypto data, including BTC, for the POC and preprocessed it to determine a suitable timeframe showing if the data is stationary (ADF test). We determined the best parameters using autocorrelation/partial autocorrelation plots and determined the best fit using AIC. Finally, we created a future dataframe for prediction and visualization. Following is the description of each parameter in the SARIMA equation:



Prediction and model fit on monthly BTC data:



Model Fit and Prediction

Backtesting confirms ARIMA's inability to outperform B&H, while SARIMAX is on-par.

Buy and Hodl:

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$2000000B	$1,640,017.87	-$3,484.66	$0.00	$1,543,502.69	31.031%	1,540.02 %	$0.00	$1,742,208.77

ARIMA:

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$240000B	$165,844.04	-$532.70	$0.00	$66,376.75	4.043%	65.84 %	$0.00	$266,151.74

SARIMAX:

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$110K	$1,634,062.66	-$3,472.73	$0.00	$1,537,535.54	30.941%	1,534.06 %	$0.00	$1,736,241.62

Backtest results

Summary of the best model selected using AIC:

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                            Close_box   No. Observations:                 61
Model:             SARIMAX(1, 1, 0)x(2, 1, 0, 12)   Log Likelihood                 102.596
Date:                              Sat, 03 Dec 2022   AIC                           -197.192
Time:                                      20:39:53   BIC                           -189.707
Sample:                                  11-30-2017   HQIC                          -194.364
                                       - 11-30-2022
Covariance Type:                                opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.4797      0.077      6.244      0.000       0.329       0.630
ar.S.L12      -0.4682      0.221     -2.120      0.034      -0.901      -0.035
ar.S.L24      -0.5576      0.121     -4.622      0.000      -0.794      -0.321
sigma2         0.0007      0.000      4.794      0.000       0.000       0.001
===================================================================================
Ljung-Box (L1) (Q):                   1.13   Jarque-Bera (JB):                14.45
Prob(Q):                              0.29   Prob(JB):                         0.00
Heteroskedasticity (H):               0.19   Skew:                            -0.67
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.33
===================================================================================
```

Best model output

We conclude that SARIMA is close to B&H because it considers a *rolling window* for auto/partial correlation along with seasonal changes to regression parameters; thus, it maintains the latest trends for prediction. Also, ARIMA is not profitable for unstable (non-stationary) markets like crypto.

Conclusions and Future Work

Overall, each study of CORRMA and the respective trading algorithm showed strong potential. There are various future considerations that we'd like to explore:

- Deeper in-sample vs. out-of-sample backtesting
- Develop more algorithms (i.e., time to stay out of the market).
- SARIMA model extended to include eXogenous features

As a retail trader, if you are fine with the risks associated with holding EITHER asset for the long run, it might be better to use this CORRMA algorithm. Based on our optimized results, we at least perform about as well or much better than B&H with large upside potential.

OUR DATA AND RESOURCES:

GitHub: https://github.com/joshcaskie/478-marketbusters

Strategy Backtesting Sheet:

https://docs.google.com/spreadsheets/d/1crSXA8EVWAYZEFZIHKW3_GZTUM4e8Z4DNVAMQu4QANU/edit?usp=sharing

Final Presentation Slides:

https://docs.google.com/presentation/d/1GpWc5je-Q5FDnF0MsXeYrRv5RKLmwnlG/edit?usp=sharing&ouid=107033263361997095008&rtpof=true&sd=true

PRIMARY REFERENCES:

[1] QuantConnect. Intraday Dynamic Pairs Trading using Correlation and Cointegration Approach. https://www.quantconnect.com/tutorials/strategy-library/intraday-dynamic-pairs-trading-using-correlation-and-cointegration-approach

[2] Pollet, Joshua M, and Mungo Wilson. "Average Correlation and Stock Market Returns." *Journal of Financial Economics*, ScienceDirect, 24 Feb. 2010, https://www.sciencedirect.com/journal/journal-of-financial-economics.

[3] Shapira, Y., et al. "The Index Cohesive Effect on Stock Market Correlations." *The European Physical Journal B*, vol. 72, no. 4, 2009, pp. 657–669., https://doi.org/10.1140/epjb/e2009-00384-y.

SECONDARY REFERENCES

Bhat, Shripad. "ARIMA/SARIMA with Python." *Data Science*, 1 Jan. 2019, www.datasciencesmachinelearning.com/2019/01/arimasarima-in-python.html.

Flavin, Thomas J, et al. "Explaining Stock Market Correlation: A Gravity Model Approach." *The Manchester School*, vol. 70, no. S1, 2002, pp. 87–106., https://doi.org/10.1111/1467-9957.70.s1.5.

Kwapień, J., et al. "The Bulk of the Stock Market Correlation Matrix Is Not Pure Noise." *Physica A: Statistical Mechanics and Its Applications*, vol. 359, 2006, pp. 589–606., https://doi.org/10.1016/j.physa.2005.05.090.

Wichard, Jörg D., et al. "Detecting Correlation in Stock Market." *Physica A: Statistical Mechanics and Its Applications*, vol. 344, no. 1-2, 2004, pp. 308–311., https://doi.org/10.1016/j.physa.2004.06.140.

DATA REFERENCES

https://coincodex.com/crypto/bitcoin/historical-data/ - Cryptocurrency data

https://fmpcloud.io/documentation/#historicalCryptoData - Cryptocurrency data

https://www.alphavantage.co/ - Stock, ETF, and Cryptocurrency data

DOCUMENTATION REFERENCES

QuantConnect:

1. https://www.quantconnect.com/docs/v2/research-environment/indicators/custom-indicators
2. https://github.com/QuantConnect/Lean/blob/master/Algorithm.Python/CustomIndicatorAlgorithm.py
3. https://www.quantconnect.com/docs/v2/writing-algorithms/indicators/custom-indicators#02-Define-Indicators
4. https://www.quantconnect.com/docs/v2/writing-algorithms/indicators/key-concepts#01-Introduction

Class Resources and Example Code by Prof. Zhen Liu

Technical Appendix

CORRMA Research

Research into the correlation moving average indicator began with a Jupyter notebook file and methods developed within. First came a general *corrMA()* method which has the parameters of a dataframe, the window, the independent asset, and the dependent asset(s). This method computes the rolling correlations for a historical timeframe. Analysis began with 5-year crypto historical data.

Next, this shifted into the development of a fully-fledged corrma_analysis() method which takes a dataframe, window, corr_ratio/threshold, independent asset, and dependent asset. It returns various pieces of data associated with the period and a variety of charts. Please peruse the samples in our GitHub repo here:
[**https://github.com/joshcaskie/478-marketbusters/blob/main/CORRMA%20and%20SARIMA%20-%20Crypto/Large%20Cap%20Crypto%20Correlation.ipynb**](https://github.com/joshcaskie/478-marketbusters/blob/main/CORRMA%20and%20SARIMA%20-%20Crypto/Large%20Cap%20Crypto%20Correlation.ipynb)

A key piece of data being returned is the first dataframe that is printed to the output. It includes data about prices and cumulative returns of each asset before CORRMA is triggered, once it drops below the threshold when it comes back above the threshold, and post-threshold. The last column includes the data regarding the % changes occurring with the independent and dependent assets during the window. Based on a few examples, there is an indication that some heavy price actions occur during these periods of low moving average correlation, which influenced our decision to backtest using QuantConnect.

Process

What to analyze for each potential strategy:

- Chance of winning
- The scale of winning (how much)
- Timeframe
- Correlation ratio
- Overall how much did we win
- How to pivot this result into a new hypothesis

Process

1. Get data
2. Clean data
3. Apply analysis via backtesting
    a. **Randomized backtesting**
4. Confirm results
5. Form new hypothesis
6. **How meaningful is our analysis? Does it show anything new? How can we explain it to other people?**

Cryptocurrencies

Thus begins the backtesting phase. We created a custom QuantConnect Indicator to track the correlation moving average over time after a waiting period. The basic CORRMA trading algorithm can be referenced here:

https://github.com/joshcaskie/478-marketbusters/blob/main/QuantConnect%20Backtesting/corrma_basic.py

After confirming the viability of the script and creating a benchmark script (**https://github.com/joshcaskie/478-marketbusters/blob/main/QuantConnect%20Backtesting/benchmark.py**), we were ready to begin testing the algorithm:

Regarding data collection, we have organized our results in a Google Sheet accessible here: https://docs.google.com/spreadsheets/d/1crSXA8EVWAYZEFZIHKW3_GZTUM4e8Z4DNVAMQu4QANU/edit?usp=sharing

1.1.1 - Novel analysis. Can we outperform a BTC buy-and-hold strategy?

For this test, we input various windows and a corrma threshold of 0.3. And success! It outperformed BTC's benchmark for CORRMA(30, 0.3). However, upon testing other variations of windows and thresholds, it became more apparent that as the ratio got larger, the profitability increased more and more. This led to the eventual realization that we had forgotten to consider the ETH benchmark, which shows that holding ETH for the same window would have turned 100k into 13M vs. attempting the strategy. This hypothesis failed to beat B&H.

BTC Benchmark:
https://www.quantconnect.com/terminal/processCache/?request=embedded_backtest_8385d498625040e95192e164b4e1d0e0.html

ETH Benchmark:

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_bdafbd593ed78e0731efefeabcf29e03.html

BTC v. ETH and CORRMA(30, 0.3):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_43b7a82585b58cde4b6706cbf4fb14c7.html

1.1.2 - Complete divergence CORRMA

Next, I adjusted the parameters to have a corrma threshold of 0. The motive was to see if, when completely diverging, swapping from BTC to ETH would be a profitable trade for those periods and allow for capturing large gains. This was unsuccessful and failed to beat the benchmarks.

BTC v. ETH and CORRMA(30, 0.0):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_e3c08372b7e22b251b1d2a7b9e188f3b.html

1.1.3 - Changing the time frame

Next involved moving the timeframe up 1 year to start on 1/1/2018 vs. 1/1/2017. The overall returns drastically decreased for the benchmarks indicating that 1 missing year would have turned 100k into extra millions for being in the market.

This is when we noticed our first minor breakthrough. Not accounting for fees, the net profit of CORRMA(30, 0.3) for BTC v. ETH was greater than that of both benchmarks (50k vs. 17k and 46k respectively). This indicated we were on the right track.

Since this was successful, we also tested 30 days with a variety of other threshold values, but this was even worse than buy and hold.

BTC Benchmark:
https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_2d01827fe566f59cc94d472d7a3513a9.html
ETH Benchmark:
https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_17b3734c8e8e0d5def13cafa87d1a331.html
BTC v. ETH and CORRMA(30, 0.3):
https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_5dd34f45ce734d96f095d3b89e25d3c5.html

1.1.4 - Swapping the original asset

Further down the sheet marks the results for a new hypothesis. Since ETH was a better-performing asset than BTC, it might make more sense to hold it as the initial asset to capture more gains.

The results were alarming. For ETH v. BTC of CORRMA(10, 0.3), net profit was above the benchmarks by 130k. But the next check of CORRMA(90, 0.3) broke all expectations, having a net profit of 36 million, 23 million above ETH's buy and hold benchmark. We knew we had stumbled upon something major here.

This marks a fundamental shift in our hypothesis. Originally, we wanted to outperform a buy-and-hold strategy of holding "the market" (i.e. in crypto's case, the larger market cap coin). So, we'd start by buying it, then swapping to a new (smaller) asset to attempt profits on volatile swings.

But, we now have a new hypothesis: We want to outperform a buy and hold of the SMALL asset (in the market cap sense). So, we can use correlation to try and hedge our large losses while staying in the small asset by swapping to the (theoretically) less volatile large asset.

ETH v. BTC and CORRMA(10, 0.3):
https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_1380b54f051b622edd357005e6b7db79.html
ETH v. BTC and CORRMA(90, 0.3):
https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_593d133b1803363ab1716a47d97edfd7.html

1.1.5 - Adjusting the algorithm trading criteria

This hypothesis involved testing a new version of the algorithm centered around CORRMA:

https://github.com/joshcaskie/478-marketbusters/blob/main/QuantConnect%20Backtesting/corrma_advanced.py

Parameters:

- *window* = rolling time frame for correlation computations
- *threshold* = correlation threshold to trigger an action

Advanced Algorithm:

- If corrma drops below the threshold, swap to the dependent asset.
- If corrma drops below 0, swap back to the original asset.
- Once it regains value, swap back to the dependent/original respectively.

This test did not work successfully. When comparing QuantConnect optimizations run to find the ***best*** combination of *window* and *threshold* parameters, the original algorithm slightly outperformed the advanced one.

Advanced best performers:

Backtests

PSR	Sharpe Ratio ↓ ≡	Net Profit	Drawdown	window	threshold
79.84%	2.286	46,806.66	90%	120	0.8
78.359%	2.237	41,498.521	85%	150	0.8
78.198%	2.235	41,329.324	88.1%	130	0.8
77.684%	2.211	38,819.559	85.1%	110	0.8

ETH v. BTC Advanced and CORRMA(120, 0.8):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_fd1a431961555e5937862a864e653c87.html

Basic best performers:

Backtests

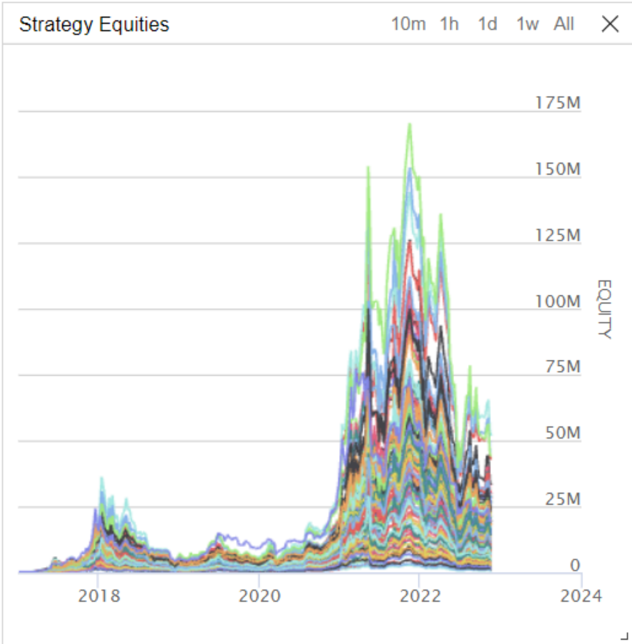
PSR	Sharpe Ratio	Net Profit	Drawdown	window	threshold
80.692%	2.314	50,230.75	90%	120	0.8
79.568%	2.276	45,719.195	85%	150	0.8
79.292%	2.267	44,919.606	88.1%	130	0.8
78.379%	2.23	40,783.048	85.1%	110	0.8

ETH v. BTC Basic and CORRMA(120, 0.8):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_898fdff8a46e6bfb9ad8b7edcc49b930.html

1.1.6 - QuantConnect Optimizations

This process was already started in 1.1.5, but the overall idea and importance of this hypothesis/method is worthy of discussion. It helped us find the optimal combination of parameters for an in-sample backtest for the trading algorithm. QuantConnect ran multiple simulations simultaneously adjusting the parameters to allow us to find the best ETH v. BTC parameters.

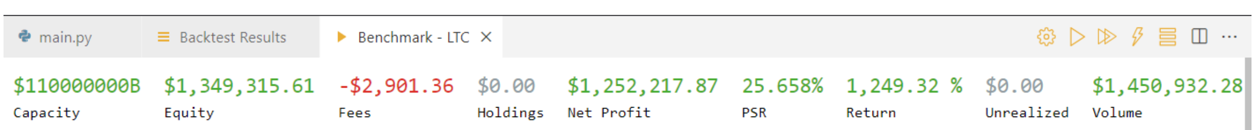


1.1.7 - Comparing results with other cryptocurrency pairs

To try and break out of the in-sample testing, we took the optimal results from the ETH v. BTC tests and applied them to two completely different crypto pairings for the same period. LTC v. BTC and ZEC v. BTC. Both showcased very successful results.

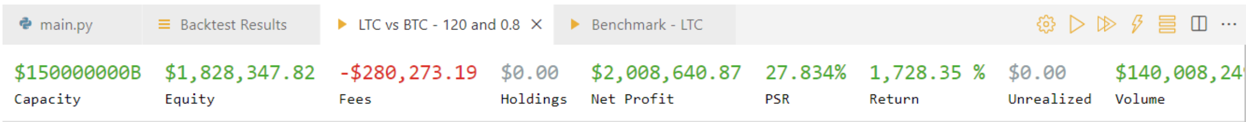
LTC Benchmark:

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_9fdc942dcbe01bcfc37f6c8a1e52756e.html



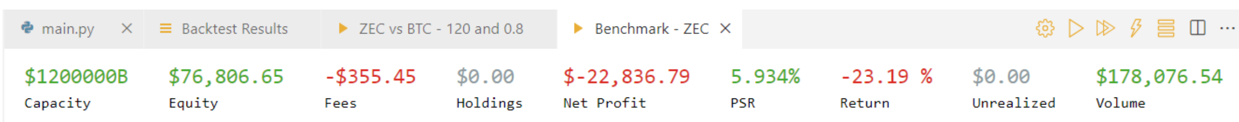
LTC v. BTC and CORRMA(120, 0.8):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_875158c558b7ccda5594b524b410f30f.html



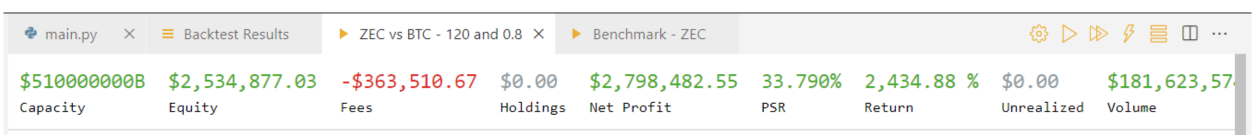
ZEC Benchmark:

[https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_a800b9e47d1e9097c755e1dd93995 83c.html](https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_a800b9e47d1e9097c755e1dd9399583c.html)



ZEC v. BTC and CORRMA(120, 0.8):

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_dd56ddb2f62444b50ec9149a4a8ede94.html



1.1.8 - In-sample vs. out-of-sample testing

To attempt to gain some more insight into the validity of the results (which seem extravagant and particular to these crypto pairs specifically), we attempted to generalize the algorithm and "train" on 4 years worth of data from 1/1/2017 to 11/22/2021, using the QuantConnect optimizer to find the best parameters, then ran an out-of-sample test to simulate "live trading" based on our training data. The results are as follows:

BTC B&H 11/22/2021 to 11/22/2022 (1 year)

Backtest Results | ETH B&H 11/22/21 to 11/22/22 | BTC B&H 11/22/21 to 11/22/22

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$78000B	$27,596.14	-$253.51	$0.00	$-72,150.35	0.211%	-72.40 %	$0.00	$126,556.89

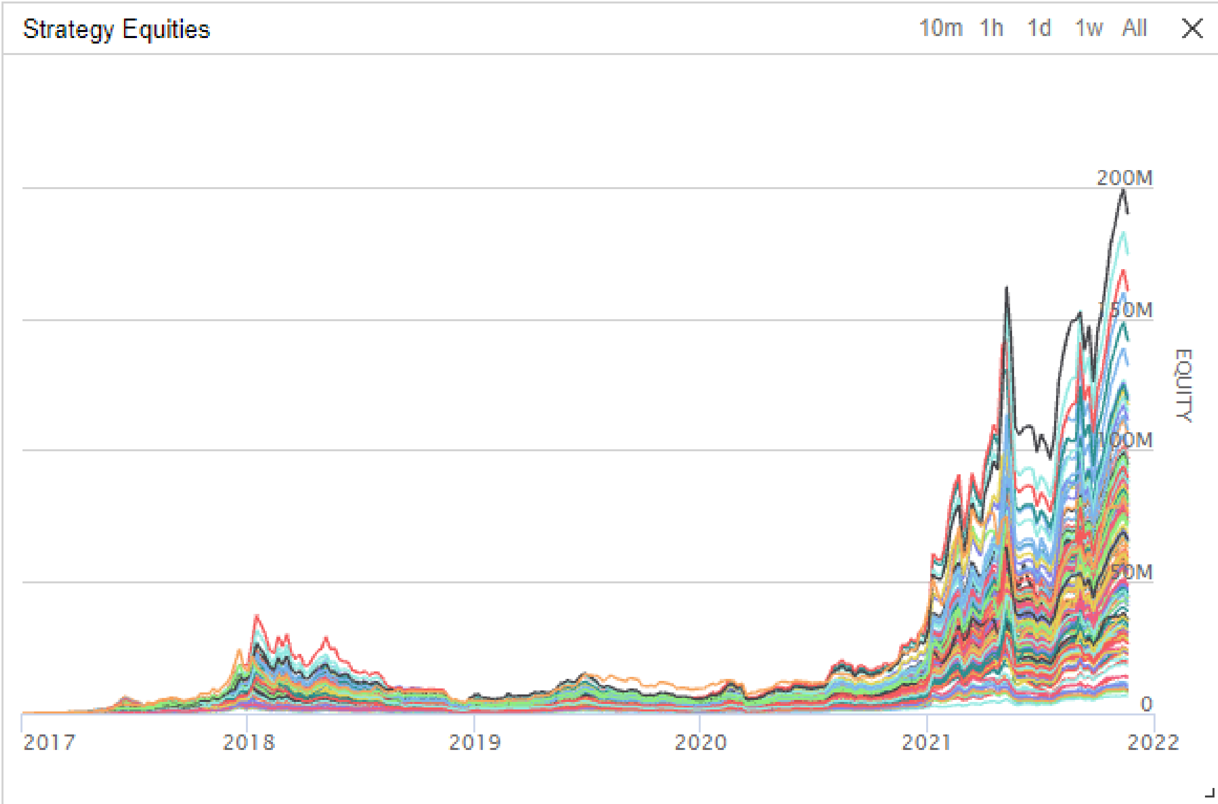
ETH B&H 11/22/2021 to 11/22/2022 (1 year)

Backtest Results | ETH B&H 11/22/21 to 11/22/22 | BTC B&H 11/22/21 to 11/22/22

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$410000B	$25,710.56	-$249.70	$0.00	$-74,039.71	1.074%	-74.29 %	$0.00	$124,664.14

Overall these losses are to be expected for an initial $100,000 investment at the peak of the recent crypto bull run to fall into crypto winter today.

ETH v. BTC 1/1/2017 to 11/22/2021 ~ 4 year training optimization:



Best performer:

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_3f6f177ac45652cf416fe8517796406f.html

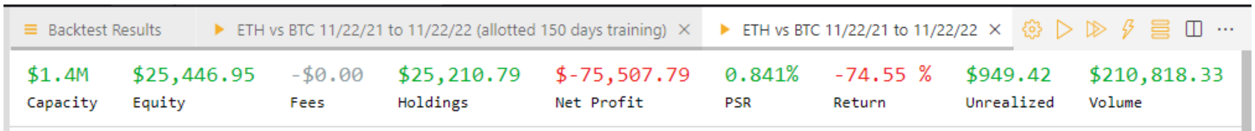
PSR	Sharpe Ratio	Net Prof... ↓	Drawdown	window	threshold
96.421%	3.695	186,065.657	84.7%	150	0.8
96.062%	3.634	170,963.149	87.8%	130	0.8

Backtest Results × | ETH vs BTC 4 year optimization | Upgraded Fluorescent Orange Hamster ×

Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized	Volume
$460K	$186,165,656.67	-$0.00	$192,914,458.05	$189,375,757.58	96.421%	186,065.66 %	$-3,336,759.44	$1,254,443,694.12

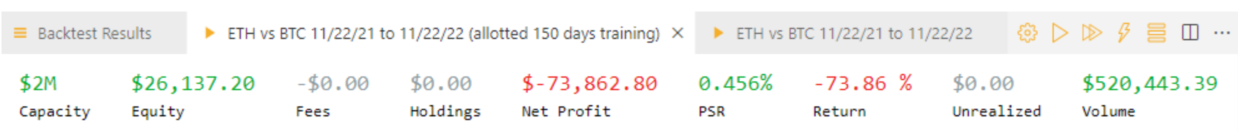
ETH vs. BTC and CORRMA(150, 0.8) for 11/22/2021 to 11/22/2022:

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_8f59a7ab4846bbdce3133822853d8f03.html



Since the window is so long, this means it buys and holds the original asset (ETH) for 150 days before it trades, i.e., the algorithm loses a lot of trading time for 1 year worth of potential. To account for this, we adjusted the algorithm to train on 150 days of prior data and *then* start trading on day one of the year by buying the original asset.

https://www.quantconnect.com/terminal/processCache?request=embedded_backtest_1a51914d7bfc87a9c267af3a48b4c583.html



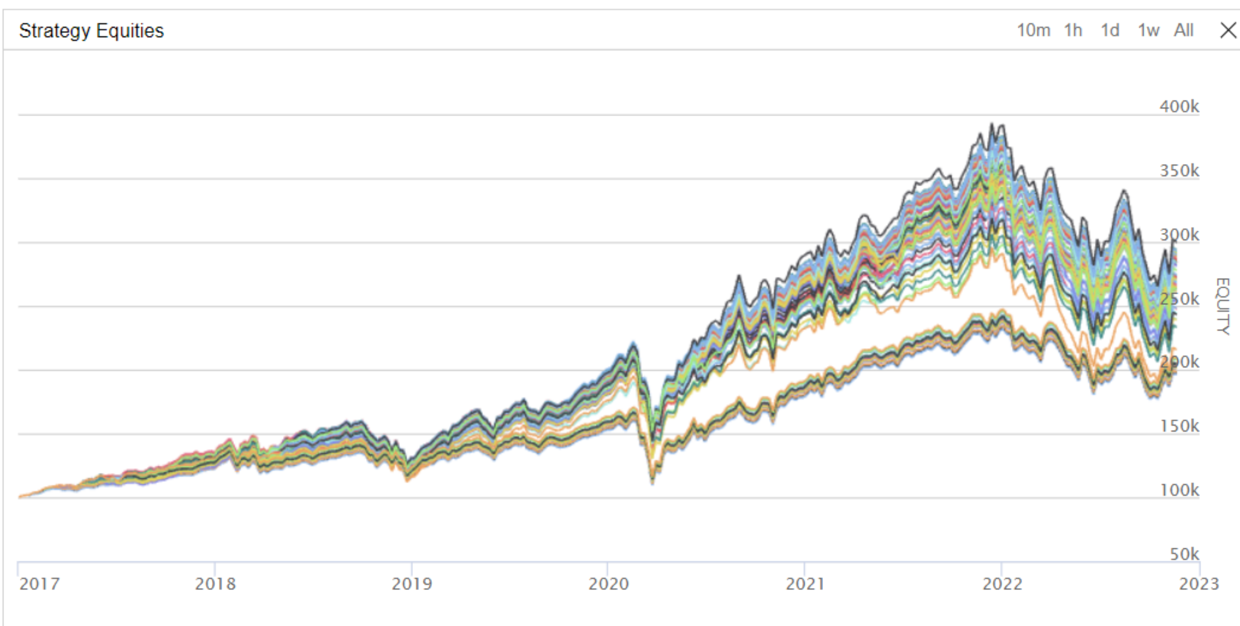
Both of these out-of-sample backtests perform worse than the B&H BTC strategy. (i.e. they lose less).

Conclusions:

- Based on the testing performed, using the basic CORRMA algorithm with a higher window and higher threshold is generally more successful in the crypto world.

- The out-of-sample results affirm the thought that more defined testing is needed. There should be tests for different time ranges. The algorithm might only be beneficial during more volatile bull runs, and might not be able to distinguish better trades during the bear cycles. However, another theory is that the entire crypto market has fallen at a remarkably similar pace and the correlation is probably very tight so the algorithm can't find a better coin to stay in with such a long *window*.

Stocks and Sectors



This image shows the results of running an optimizer to determine the best window size and corresponding corrma threshold that maximizes the profit for XLK vs SPY. When analyzing results, we excluded any findings that held one stock and never touched the other one. The way that we determined which pair of window size and corrma threshold was the one with the highest net profit. Once we got the optimized window and corrma threshold, we used it and manipulated the time frames to test if those values are still optimal. The corrma threshold and window size that we found was the most optimal for this pair of stocks is 150 days and an 0.8 ratio. We found that when you start with sector stocks and transition to the larger market, the optimal pair is a higher window size and a higher corrma threshold.

Name	Start	End	Window	Corrma	Initial Capital	End Equity	Fees	Net Profit	PSR	Returns
XLK Benchmark	7/4/2007	7/1/2009	x	x	$100,000	$71,784.13	-$48.09	-$28,167.78	1.59%	-28.22%
SPY Benchmark	7/4/2007	6/1/2009	x	x	$100,000	$63,249.07	-$8.84	-$36,742.09	0.78%	-36.75%
XLK vs SPY	7/4/2007	7/1/2009	150	0.8	$100,000	$74,913.78	-$169.16	-$24,917.06	1.97%	-25.09%
XLK Benchmark	1/1/2000	11/1/2022	x	x	$100,000	$307,725.86	-$24.30	$207,750.16	0.00%	207.73%
SPY Benchmark	1/1/2000	11/1/2022	x	x	$100,000	$397,887.72	-$10.32	$297,898.04	0.01%	297.89%
XLK vs SPY	1/1/2000	11/1/2022	150	0.8	$100,000	$377,112.33	-$511.76	$277,624.09	0.00%	277.11%
XLK Benchmark	9/23/2019	9/1/2022	x	x	$100,000	$171,826.61	-$12.76	$71,839.37	22.27%	71.83%
SPY Benchmark	9/23/2019	9/1/2022	x	x	$100,000	$137,877.38	-$3.50	$37,880.88	14.41%	37.88%
XLK vs SPY	9/23/2019	9/1/2022	150	0.8	$100,000	$176,499.70	-$47.39	$76,547.09	23.90%	76.50%

XLK vs SPY for various timeframes

This figure shows the results of comparing XLK and SPY for different periods. The time frames that we tested were the 2008 recession, the covid window, and also a 20-year window. We started by finding the benchmark values of XLK and SPY for each timeframe and then tested corrma for XLK vs SPY and compared those results to the benchmark. We found that if the time frame is smaller than the original testing period of 5 years, the corrma would outperform both benchmarks. When we used corrma on a larger period than that of the testing period, it is found that corrma usually outperformed one benchmark but not the other.

2008 Recession

When calculating the benchmarks for the timeframe of the 2008 recession, the results showed that you would lose money based on the window and corrma threshold. After performing the correlation moving average on XLK vs SPY, the results showed that we would still lose money but the amount of loss is less than the benchmarks. We can conclude from these results that if both benchmarks and the results from corrma are all negative profits, to outperform the benchmarks the corrma results need to have a smaller number.

20+ year timeframe

When comparing the results that we got after computing the benchmarks and corrma for this time frame, we found that the corrma results outperformed the sector stock but not the larger market stock. A conclusion that was made was that the optimal values that we found, in the beginning, were for a timeframe of 5 years and if we choose to test it on a timeframe larger than 5 years, it might require us to recalculate the optimal window size and corrma threshold.

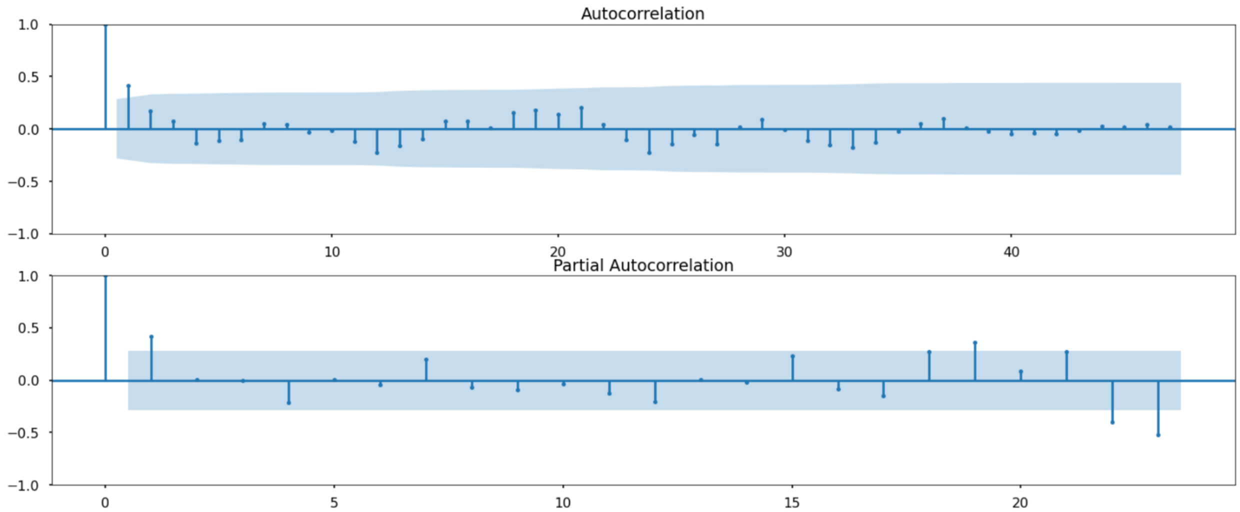
SARIMA

AutoRegressive Integrated Moving Average is a statistical model consisting of 3 terms:

- AR = p term (autoregressive)
- I = d term (differencing)
- MA = q term (moving average window)

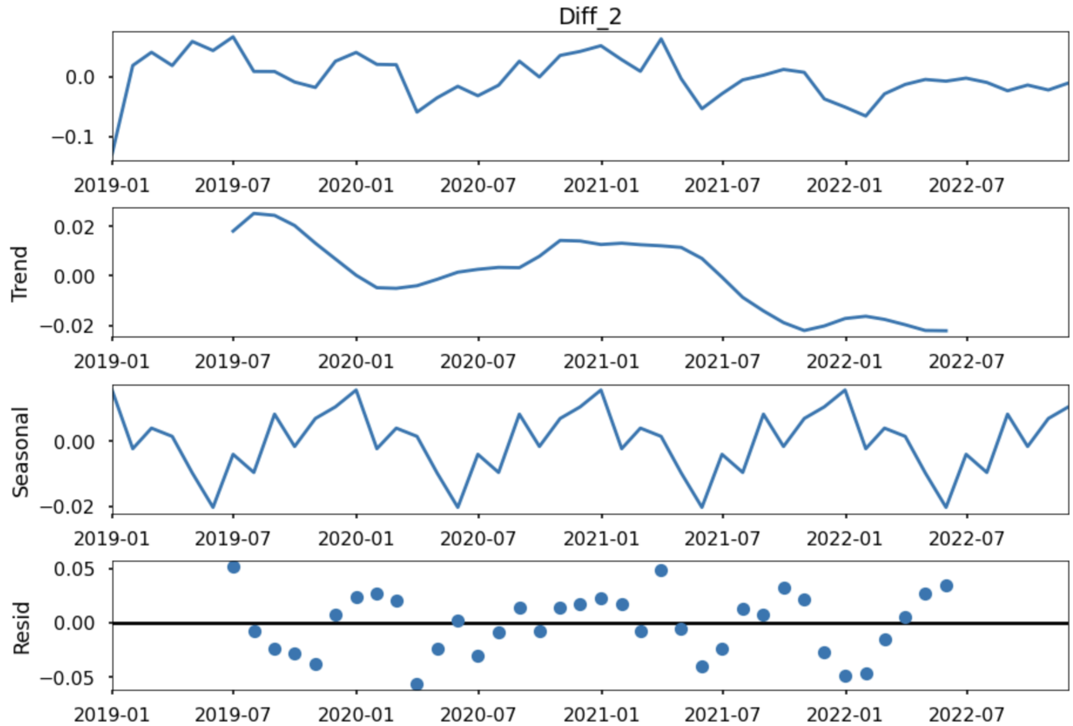
The value of p determines how many historic prices is the current time series variable dependent on. The d term refers to the order of differencing, required when the series is non-stationary. The q term simply means the window of moving average.

Autocorrelation and partial autocorrelation plots to determine possible ranges of q and p terms respectively:



Augmented Dickey Fuller (ADF) Test:

Used to check the stationarity of data meaning the mean and variance of time series variables do not change over time. This step is necessary because: if we wish to forecast the future, fitting a decent model to stationary data will enable us to do so with accuracy because the model's statistical features are constant over time.



ADF test checks if data is stationary by testing the null hypothesis that unit root (meaning trend) is present in it and the trend is stationary.

Akaike's Information Criterion (AIC):

Used to determine if the parameters are valid for fitting the regression equation. We also get the best model with the value of AIC (the lesser the better).

SARIMA[X] stands for Seasonal AutoRegressive Integrated Moving Average with eXogeneous features. These are nothing but the external features that affect the dependent variable in the real world.