ITIC

PAIRS TRADING WITH TOP 200 CRYPTOS

Return: 241.16%

Volatility: 30.99%

Sharpe Ratio: 7.78

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Pairs Trading with Top 200 Cryptos

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INTRODUCTION

The main goal of this report is to state the process and the conclusions that our team at the Quantitative Strategies Department achieved while developing a portfolio-building technique using a known trading strategy of Pairs Trading for the Top 200 cryptocurrencies ordered by Marketcap Value.

In simple terms, pairs trading looks into two securities with a high cointegration to each other and proceeds to open a matching long position with a short position when the correlation between the two securities temporarily weakens with the expectation that the spread between these two highly cointegrated securities will, sooner or later, converge to the mean.

This idea was first developed by the quantitative group at Morgan Stanley in the 1980s led by Gerry Bamberger and Nunzio Tartaglia and is categorized as a statistical arbitrage and convergence trading strategy.

This research goes over multiple steps. The first one is to analyze if the two different cryptocurrencies are co-integrated. In the second step, we apply the trading strategy, defining when we should long or short a pair of stocks based on their cointegration. The last step is to build and optimize a portfolio that maximizes the return for each unit of risk, also known as Sharpe Ratio.

METODOLOGY

The first step of this research will be the analysis of the co-integration between two different cryptocurrencies. This statistical test will be performed for every possible pair of two different cryptocurrencies from the top 200 biggest ones in the market. From a total of 19,900 possible pairs with data from the last 2 years, only 3,104 passed the test and can be considered as cointegrated stocks.

Calculation

$$C(n, r) = C(200, 2)$$

$$= \frac{200!}{(2!(200-2)!)}$$

$$= \frac{200!}{2! \times 198!}$$

$$= 19900$$

Number of combinations: 19,900

With the goal of analyzing the spreads between two cryptocurrencies and test for the stationarity in a time series, it will be necessary for us to get the data from all the 200 cryptocurrencies. To get this data, we used a Python API from Yahoo called yfinance. Given a ticket and a time frame, this API allows us to download the data relative to the cryptocurrencies price over time. We choose to use the *Adj Close* (Adjusted Close) variable that was available to us in the data previously downloaded.

For two stocks to be considered co-integrated, it is necessary that the spread is tested and confirmed as stationary in a time series. To calculate the spread, we previously developed a function that computes the difference between two values over time and saves the data as a time series.

To run this statistics test in the pairs, we applied the Dickey–Fuller test, where the alternative hypothesis confirms the stationarity of a given time series. For every pair that does not cross the given level of significance of 5%, meaning that the null hypothesis is rejected, we consider the two stocks as co-integrated because the time series of their spread is stationary.

PORTFOLIO OPTIMIZATION

To apply a trading strategy like Pairs Trading, we are assuming that the price of stock B can be explained by the price of stock A plus and error and vice versa.

$$Price\ of\ Stock\ B = a + b * Price\ of\ Stock\ A$$

Therefore, if this condition does not hold true, we will have a trading opportunity by longing the undervalued crypto and shorting the overvalued crypto.

We will assume a Fee of 0,1% per trade and a standard threshold of -2,5 for the T-statistic and do not trade on pairs above these values.

We have done an OLS regression with the differences between prices and minimize our T-Statistic value using the Nelder–Mead method in order to optimize the minimum possible value that signifies the most robust dynamic conversion price equilibrium we can trade upon. We did this with the same process and code provided by NEDLeducation, ending up with optimized parameters for a and b, which help us calculate the fair-value of the stock and an optimized T-Statistic.

$$Fair\ Value = a_{optimized} + b_{optimized} * Price\ of\ Stock\ A$$

Therefore, if the optimized T-Statistic is lower than our threshold of -2,5 we will operate according to these rules:

$$Fair\ Value\ of\ Stock\ < Price\ of\ Stock$$

We long the undervalued crypto and short the overvalued pair crypto.

$$Fair\ Value\ of\ Stock\ > Price\ of\ Stock$$

We short the overvalued crypto and long the undervalued crypto pair.

We backtested this trading idea for 3104 pairs that were cointegrated, resulting in 3,104 different trading results that took two full days to run. After this, we build some evaluation metrics and filter these results to get a list of trading strategies with a return above 7% and Max Drawdown superior to -1 and ending up with the following list of 19 pairs:

	Total Return	Sortino	Sharpe ratio	Std	Return	Maxdraw	Kelly
BCH-USD-NEO-USD	3.4637	9.09564	3.92298	0.865082	2.4637	-0.373113	3.19857
MANA-USD-ZEN-USD	2.12851	7.49281	4.57798	0.449654	1.12851	-0.274731	5.23525
MKR-USD-TOMO-USD	3.22794	6.95231	2.67467	1.18068	2.22794	-0.454228	1.54801
CCXX-USD-GRT2-USD	1.27986	6.20627	5.42155	0.223157	0.279857	-0.194941	4.21408
ICX-USD-SYS-USD	5.60486	6.14959	6.56018	0.843706	4.60486	-0.900038	6.37062
REP-USD-WTC-USD	3.58189	5.052	3.71479	0.945381	2.58189	-0.695149	2.81052
...	...	...	...	...	...	...	...
MIOTA-USD-STEEM-USD	1.76689	1.89393	3.86115	0.439477	0.766886	-0.89596	3.6082
ELA-USD-GXC-USD	1.82745	1.85218	3.61977	0.485514	0.827446	-0.948853	3.21328
ONT-USD-NULS-USD	1.42228	1.60715	3.52842	0.383253	0.422278	-0.841413	2.39836
LTC-USD-BAT-USD	1.0959	1.27922	3.24795	0.315862	0.0959038	-0.801979	0.259639
MIOTA-USD-KNC-USD	1.09879	1.16384	2.27615	0.451986	0.0987881	-0.883961	0.140917

With the pairs of these lists, we proceed to treat each strategy as an individual asset and apply the standard Markowitz Portfolio Optimization ending up with the following allocation for 18 trading pairs.

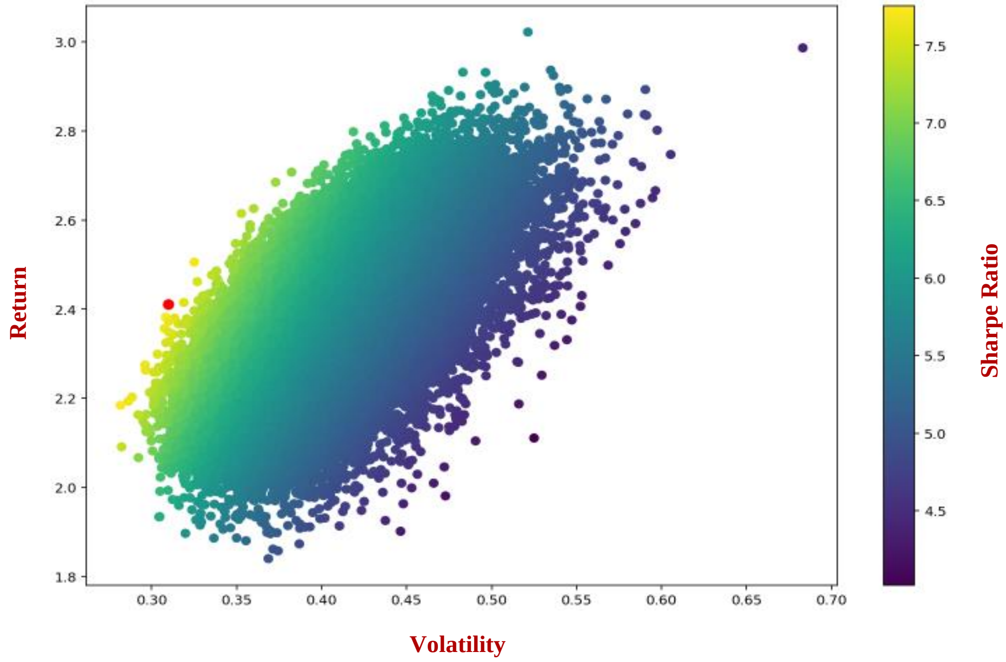

Figure 4: Markowitz Efficient Frontier visual representation

Note: This plot is just for visualization. Optimization was not based on this image.

	Weights
XRP-USD-ICP1-USD	0.0481
BCH-USD-NEO-USD	0.0951
LTC-USD-BAT-USD	0.0495
NEO-USD-XVG-USD	0.0036
MIOTA-USD-KNC-USD	0.0291
MIOTA-USD-STEEM-USD	0.0255
MKR-USD-TOMO-USD	0.1394
CCXX-USD-GRT2-USD	0.1862
TUSD-USD-QTUM-USD	0.0099

	Weights
MANA-USD-ZEN-USD	0.1604
MANA-USD-STORJ-USD	0.0786
GRT2-USD-NULS-USD	0.0152
ONT-USD-WAN-USD	0.0078
ONT-USD-NULS-USD	0.0190
UMA-USD-GXC-USD	0.0350
ICX-USD-SYS-USD	0.0242
REP-USD-WTC-USD	0.0342
WAN-USD-WTC-USD	0.0392

Figure 5: Optimal Weights

Then, we simulated the investment on these pairs according to their respective allocation as if we start with an initial portfolio of 10,000$.

Figure 6: Individual Performance of each pair on the Last Year

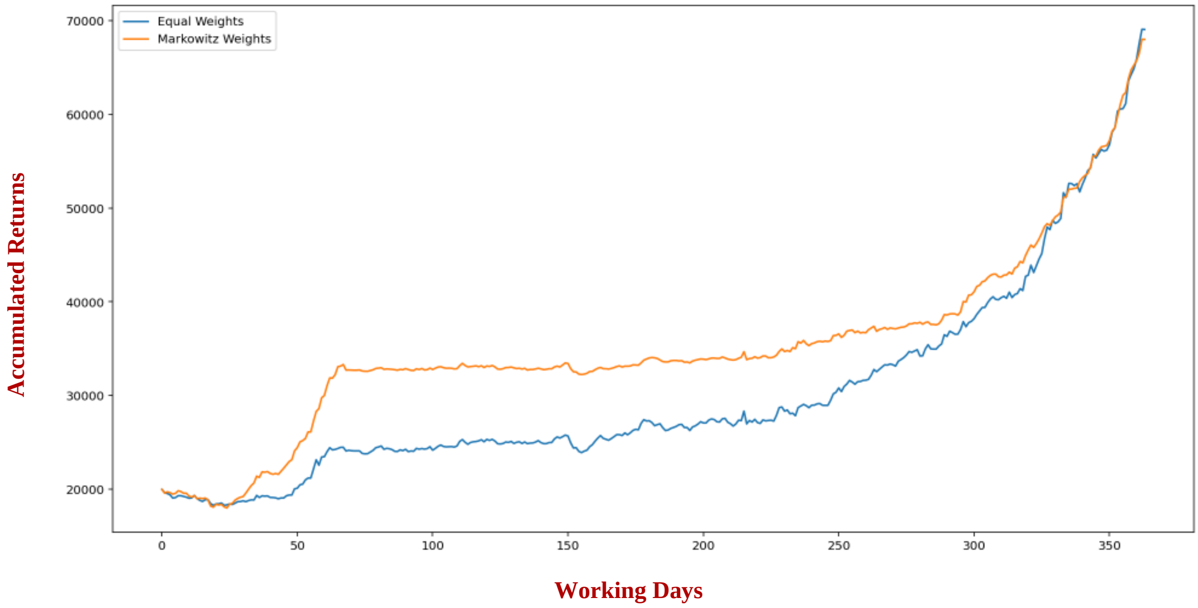

Figure 7: Accumulated Value of Portfolio on the Last Year

Although we research Kelly Leverage Multiples using the formula below for each individual strategy, we did not find it has made significant improvements on the portfolio based on our risk tolerance and goals as some of the individual strategies would completely vanish due to the drawdowns that occur. Therefore, our team decided to proceed with an unleveraged portfolio.

$$f = \frac{ExpectedReturn_a - RiskFreeRate}{Votalility_a^2}$$

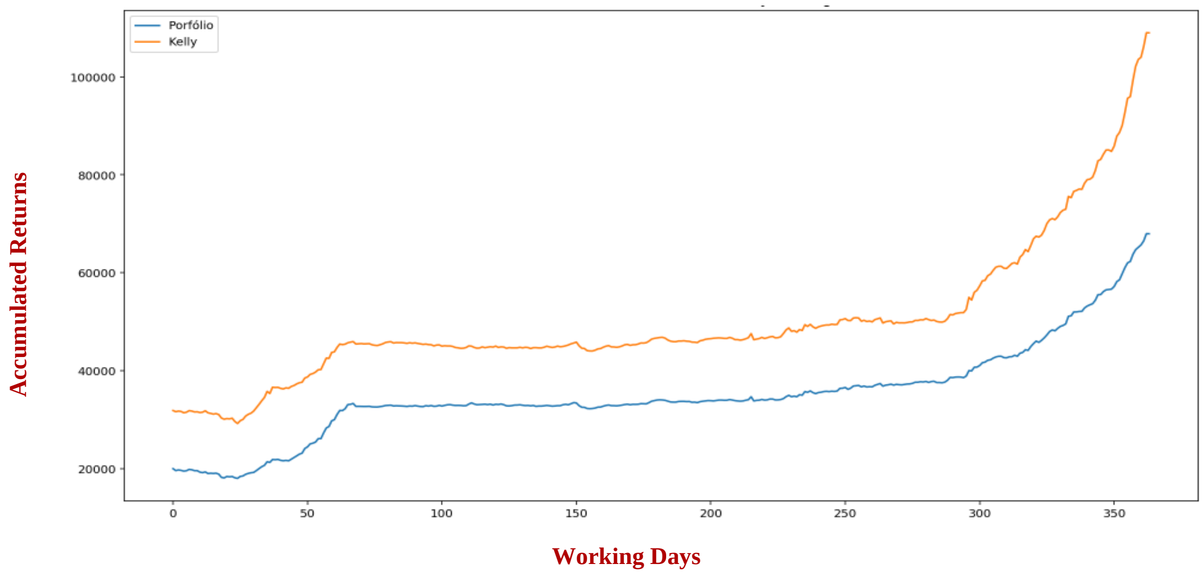

Figure 8: Accumulated Value of Portfolio with Kelly Leverage

With this said, we end up with a final portfolio with these key metrics:

Metric	Value	Confidence Level	Value at Risk
Return	2.41156	90%	-0.00492352
Volatility	0.309897	95%	-0.00716354
Sharpe Ratio	7.7818	99%	-0.0173149
Max Drawdown	-0.0691352		

Due to the high diversification of our portfolio, we were able to achieve a very smooth yield curve for our overall Strategy achieving a total return of 241,17% in one year with a max drawdown of 6.91%. The annualized volatility for this trading strategy is 30,99% and therefore we have a 7,78 Sharpe Ratio, assuming the risk-free is 7%, the assumed SP500 average annualized return.

Regarding the VAR analyses, the results are in conformity with the Max Drawdown value. When performing our tests, we can say with a 90% confidence level that the worst daily loss will not exceed 0.49%; 95% confidence level that the worst daily loss will not exceed 0.72%, and with 99% confidence that we will not surpass a daily 1,73% loss which means we have a very low-risk strategy overall that fits our department risk tolerance and goal.

MARKET VOLATILITY IMPACT

After testing our pairs trading strategy in the cryptocurrency market, we decided to analyze the performance and the impact of the volatility of the market. This analysis was performed with the goal of looking for the best way to optimize the strategy.

Analyzing the accumulative portfolio value throughout the last year, we can say that most of the time, the growth of our portfolio was low when compared with the beginning and the end of our time frame in analysis. Initially, we raised the hypothesis of our portfolio growth being affected by high volatility values during that time.

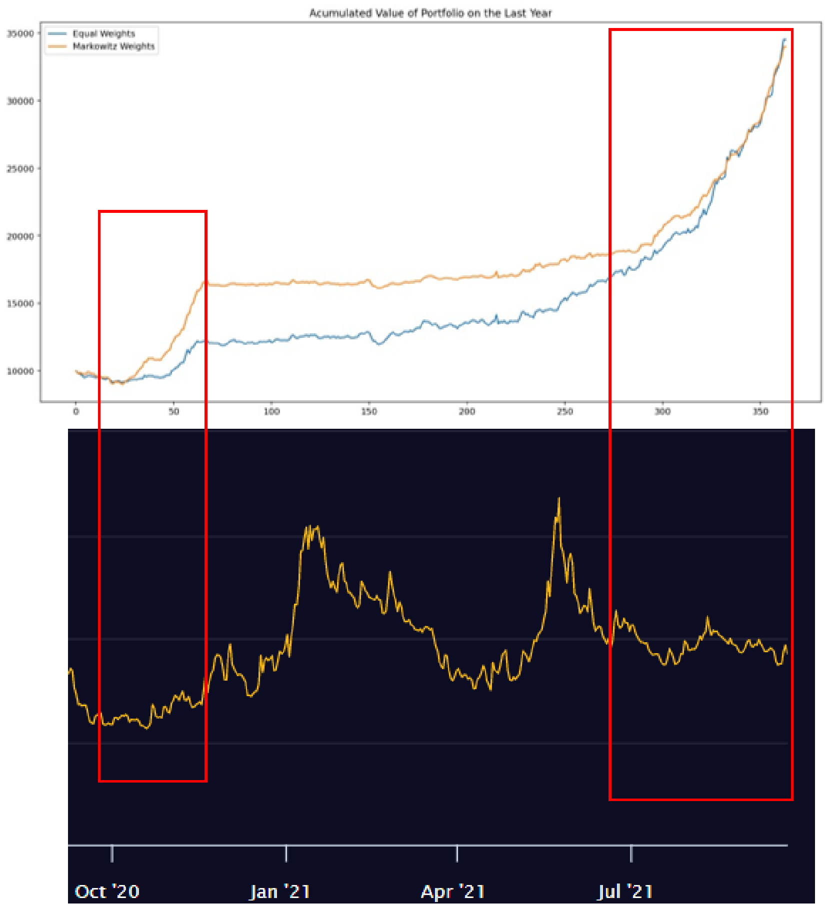

Figure 9: Crypto Volatility Index vs our Portfolio
Source: https://cvi.finance/

Using the CVI (Crypto Volatility Index), we can say that there has been some high value of volatility during that period. However, during that period, there were also registered low/normal values like the ones seen during the beginning and end of our time frame.

As we can see, the difference between the lowest and the highest volatility values in that specific timeframe is considerably superior to the values registered in the other two periods where the algorithm had a better performance. This spread in volatility value may be an indicator of market instability. When we look at that period in the crypto market, we must remember that the major cryptocurrencies lost 30% to 40% of their value in a short span of time.

Turning the analysis to another point of view, we can see that this period where our algorithm did not perform the best, matches with a period of high traded volume in the market. This might be one of the key indicators when we analyze the performance of our trading strategy.

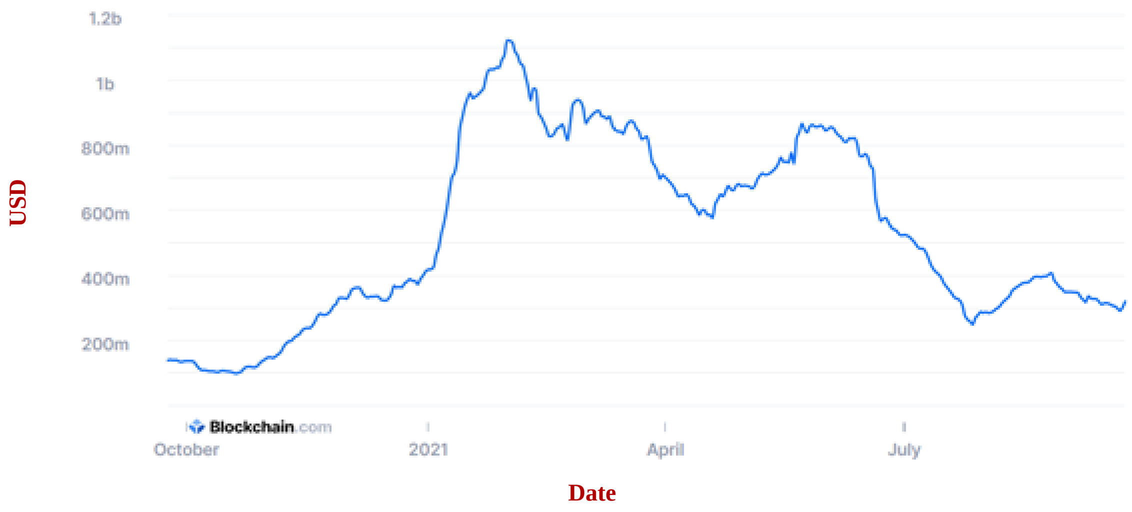

Figure 10: Bitcoin Trading Volume on the major exchanges
Source: https://www.blockchain.com/charts/trade-volume

In conclusion, we can say that this strategy will have the best performance during high volatility and high traded volume moments in the crypto market, however, this strategy performed the best when the values of traded volume were under 500 million dollars.

CONCLUSION

With this technique, we were able to build a portfolio that is not only diversified, with a variety of projects of the blockchain ecosystem, as it was able to have very above-average returns with reduced risk compared to the traditional markets.

However, we should be critical about these results and have into consideration that we used price data from last year to backtest our model and this does not mean that the cointegration between assets will hold and therefore expect to continue to have this kind of returns.

Besides this, we made several filters in order to build the portfolio which made our results positively biased. It is also important to note that we do not take into consideration slippage that will affect the overall returns of the pairs' trading strategies.

In addition, we did not check if there was the possibility to open a short position on all the assets and just described that it is possible from a theoretical perspective to build such strategies. We did not also take into consideration Futures Funding Rates, which might yield some additional results or represent a cost to have these short positions opened resulting in losses instead of profits. This is especially important, considering that some of these positions can be open for medium and long-term timeframes.

Nevertheless, the Quantitative Strategies Department will continue to follow this strategy to see if the results hold as true or if, over time, this portfolio will lose the alfa. We will test out this model with the integration of the strategy on the FTX platform with the assets that are listed in order to have some "skin in the game" and further promote knowledge about cryptocurrencies and programming skills to our department members.

Note: To get access to the full Python Code and data, contact ITIC Members.

Our Club

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