

## **Investment options diagnostic during the global pandemic**

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### **OBJECTIVE/PROBLEM**

As data scientists with a business-oriented approach, it is pertinent to analyze the trends and patterns that emerged during the COVID-19 pandemic. The outbreak of the pandemic resulted in a great deal of volatility in both traditional stocks and cryptocurrencies. In March 2020, the S&P500 recorded one of its worst days in history, experiencing a significant downturn of 12%<sup>1</sup>, which was a clear indication of the turbulence to come. However, the S&P made a remarkable recovery by August 2020 and continued to steadily increase until the beginning of 2022, after which it started to decline once again. In contrast, cryptocurrencies experienced unprecedented growth during the same period, recovering at a much higher rate than stocks. However, starting around 2022, the crypto market also started to experience a downturn.

Given these circumstances, it is essential to investigate the performance of cryptocurrency vs. stock portfolios during the pandemic. The analysis aims to assess how crypto portfolios performed during the pandemic compared to stock portfolios. The study will also investigate whether a factor investment strategy can be applied to cryptocurrency and possibly build a time-series model for crypto returns. The inquiry will provide valuable insights into the trends and patterns that emerged during the pandemic, which can be leveraged to make informed business decisions.

### **Primary Research Question**

From the start of the global pandemic (March 2020) would my money have done better overall with crypto portfolios or stock portfolios compared to the market (S&P500) and how can I maximize my returns?

### **Supporting Research Questions**

1. During this time period, was there an ideal date to invest with a particular crypto portfolio to maximize returns?
2. Could a factor investment strategy (size, value, momentum, quality, volatility) be applied to build crypto portfolio? How do these portfolios compare in terms of financial gains to the benchmarks (bitcoin/SNP500/ stock-factor specific portfolios)?
3. Can a well-performing time-series model be created to predict future crypto returns?

The crypto markets are renowned for their high degree of stochastic variance, which is responsible for significant fluctuations in prices. The intricacies of these markets have posed a great challenge for investors and machine learning models alike, as accurate price predictions remain elusive. Our analysis aims to unravel the underlying dynamics of these markets and uncover valuable insights that can aid in maximizing returns, enabling investors to earn money at a faster pace. By examining both crypto and stock risk-versus-returns ratios, we will be able to compare their respective performance and identify the most promising investment opportunities in the crypto space. Through our findings, we hope to empower investors to make informed decisions that will help them achieve their investment objectives. Our initial hypothesis was that answering each of our research questions should lead to meaningful insights in cryptocurrency investment strategies.

### **DATA**

Our Crypto dataset was pulled using Block CC API in Python. Our main dataset was a time-series daily historical price dataset for 500 cryptocurrencies over 4 + years. In addition, we pulled Market Cap, Volume, Available Supply, and Total Supply metrics for 100 coins. Similarly, the Stock time-series historical price dataset was pulled in Python from NASDAQ. Our key variable for each asset was Daily Price in USD. EDA uncovered that many of the coins in our dataset, like Solana, Polka Dot, and Shiba Inu, were newly established during our target time period. This may cause inconsistencies when comparing performance over our target time period.

### Data Cleaning

The inaugural phase of our project involved a thorough and rigorous data wrangling process. Specifically, we carefully scrutinized the cryptocurrency dataset, transforming the raw prices to simple daily returns for the different cryptocurrencies, as well as filtering it for the intended period of analysis, spanning from March 2020 to March 2023. Likewise, the stock dataset also required preliminary wrangling, with the period of interest and intervals for various stocks being gathered in a scrupulous manner. The entire process of data cleaning and transformation was meticulously executed, ensuring that the data was optimized and well-suited for subsequent analysis in the R Studio and Python environments.

## APPROACH/METHODOLOGY

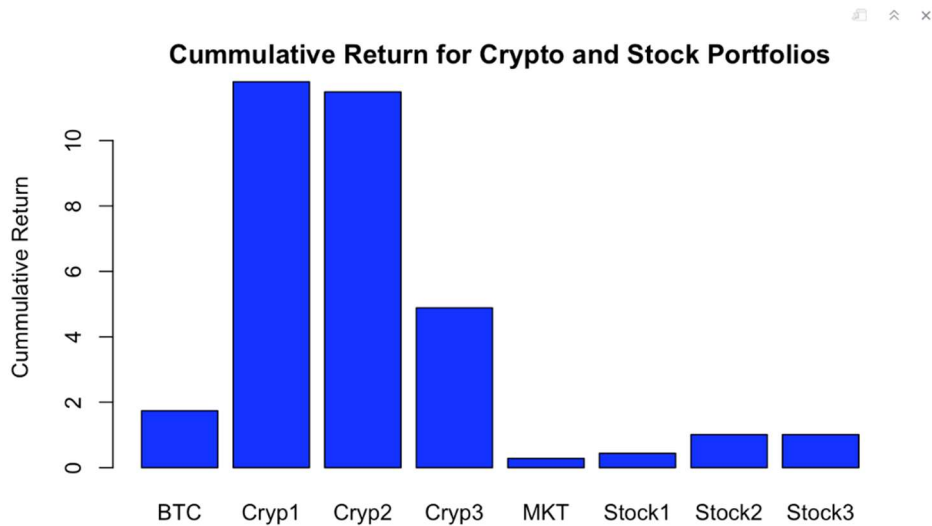
### Comparing Crypto Returns vs Stock Returns

From there, we constructed several crypto and stock portfolios composed of different assets with different levels of risk. These portfolios were then compared to a benchmark to test performance against the market. Many of these analytical tests were conducted in R using packages such as the ones we have seen in class (PerformanceAnalytics, xts, tidyverse, etc.).

Portfolio	BTC	Cryp1	Cryp2	Cryp3	MKT	Stock1	Stock2	Stock3
<b>Assets</b>	100% Bitcoin	20% Bitcoin, 20% Ethereum, 20% Binance, 20% Ripple, 20% Dogecoin	40 % Tezos, 30% Solana, 30% Cardano	20% OKB, 20 % Monero, 20% Chainlink, 20% Decentraland, 20% Litecoin	100% GSPC	20% APPL 20% GOOGL 20% AMZN 20% MSFT 20% BRK-A	100% APPL	20% NCMI 20% EFSH 20% CURO 20% UAN 20% SBLK

**Table 1.** Breakdown of the various crypto and stock portfolios

The cumulative returns for all portfolios were calculated in R studio. The results we obtained can be seen in the figure below.



**Figure 1.** Cumulative Return bar chart of stock and crypto portfolios. Y-axis is %.

Our results show that crypto assets and portfolios performed significantly better than stock assets and portfolios for the target time period. We had hypothesized that crypto and stocks would have generally performed the same due to the financial instability caused by the pandemic. Although both outperformed the market, we can see that crypto was the best investment option.

### Applying Factor Investing to Crypto

In our quest to apply factor investing to the crypto market, we delved deeper into our analysis by attempting to construct "factor" portfolios for crypto assets. In this endeavor, we sought to translate stock factors to crypto and determine the significant indices that would provide us with insights into the performance of the crypto market. For this section of the project we focused on the top 100 coins by Size and converted the daily prices to monthly returns. Then, for each factor we defined categories and compared the cumulative returns over March 2020 – March 2023.

#### Size

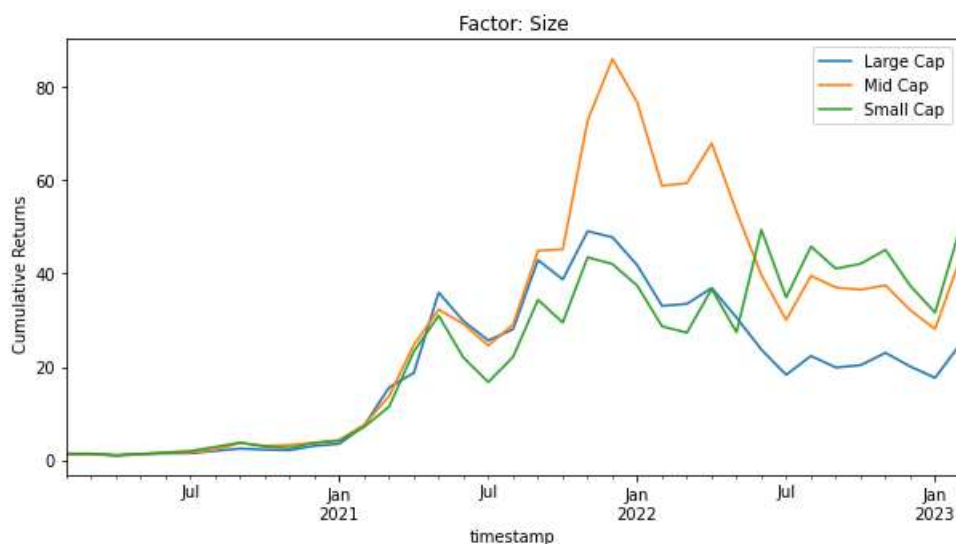
Market capitalization for crypto is defined as

$$\text{Market Cap} = \text{Current Price} \times \text{Circulating supply of a token}$$

Using the market capitalization dataset, coins were categorized just like how stocks are categorized into small and large cap. Crypto can be split into

- Large Cap: Market Cap > \$10 billion
- Mid Cap: \$10 billion < Market Cap < \$1 billion
- Small Cap: \$1 billion < Market Cap < \$100 million
- Micro Cap: \$100 million < Market Cap < \$10 million
- Nano Cap: \$10 million < Market Cap

Categorizing our 100 coins resulted in: 11 Large Cap, 52 Mid Cap, and 35 Small Cap coins. We can then compare the cumulative returns of each category by constructing equally weighted portfolios.



**Figure 2.** Cumulative Return over time graph by Size.

Looking at the cumulative returns, we can see that overall, each category followed the same trends. We had hypothesized that similar to stocks, larger market cap coins would be more stable, but smaller cap assets while being riskier could lead to higher returns. Surprisingly, we found a significant gap in performance of Mid Cap coins from Q4 2021 through Q1 2022. This may be due to our dataset including coins that were newly established during our target time period and a large portion of coins being categorized as Mid Cap. In the end, our hypothesis was correct with Small Cap performing the best and Large Cap being most stable.

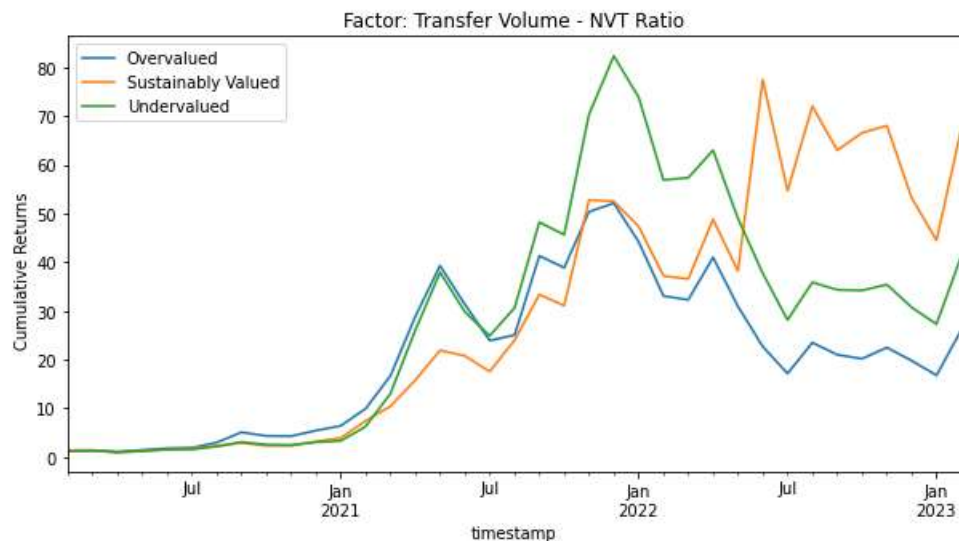
### Value

Next, we considered the value factor, which categorizes stocks as growth vs. value stocks by examining the book value relative to the market value. Since cryptocurrencies don't have a "book value," we looked at comparable crypto indices, including Network Value to Transactions (NVT) Ratio and Total Value Locked (TVL).

Network Value to Transactions (NVT) Ratio compares the Market Cap to Transfer Volume<sup>5</sup>. By calculating the average percent change over the target time period, we can categorize assets as

- Overvalued: NVT Ratio Uptrend (Market Cap growth outpaces Transfer Volume)
- Undervalued: NVT Ratio Downtrend (Transfer Volume growth outpaces Market Cap)
- Sustainably valued: NVT Ratio Sideways Trend

We categorized the coins with an average daily NVT ratio change of >2% as overvalued, <2% as undervalued, and all else as sustainably valued. This resulted in 29 Overvalued, 43 Undervalued, and 27 Sustainably Valued coins.



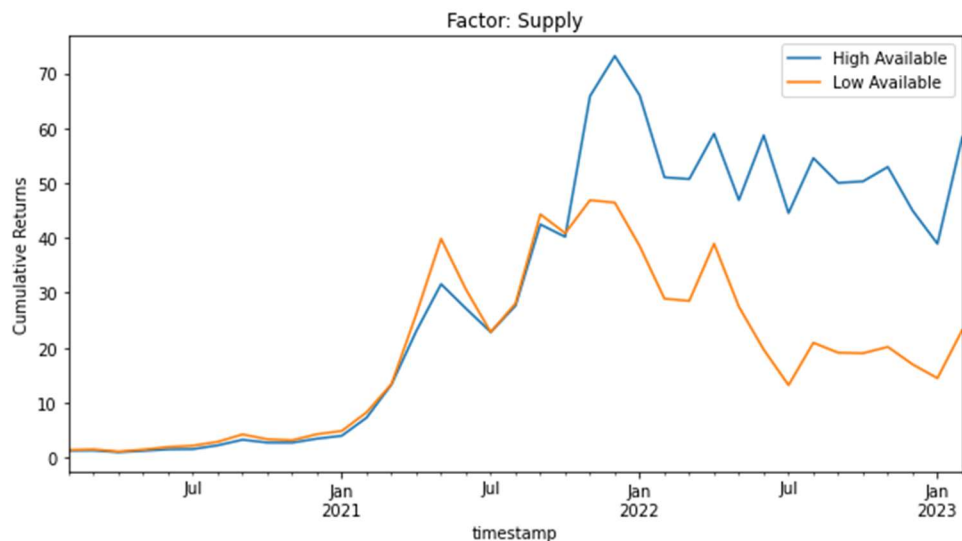
**Figure 3.** Cumulative Return over time graph by NVT Ratio.

We had hypothesized that undervalued assets would outperform overvalued assets. While undervalued coins did perform significantly better from Q4 2021 through Q1 2022, currently Sustainably Valued assets are performing the best. But, as hypothesized Overvalued assets have performed the worst of the 3 categories.

Total Value Locked (TVL) is the number of assets that are currently being staked in a specific protocol<sup>4</sup>. By comparing the Market Cap to TVL we can categorize each asset as overvalued or undervalued. While TVL is a common metric among DeFi assets, it is not available for all the coins in our dataset. Instead, we explored comparable metrics of Available/Circulating Supply to Total Supply of the coin. The Total Supply is a sum of the Circulating Supply and the coins that are locked up. Here we calculated the portion of Available Supply to Total Supply and categorized each coin as

- High Available:  $\geq 50\%$  of Supply Available
- Low Available:  $< 50\%$  of Supply Available

This resulted in the 100 coins being categorized as 76 High Available and 24 Low Available.



**Figure 4.** Cumulative Return over time graph by Supply.

Calculating the cumulative returns we find that coins with High Availability have been performing better than those that have more assets locked up. Once again, it's important to note that many new coins were introduced during this time period, a majority of which were classified as High Available.

### Momentum

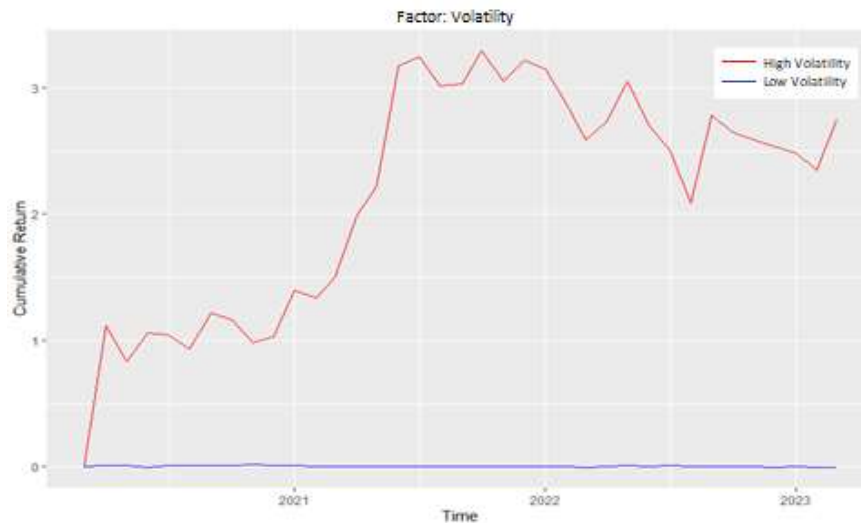
Momentum factor investing is calculated the same way for cryptocurrencies as it is with stocks. The formula is simply  $\text{Momentum} = \text{Latest Price} - \text{Closing price } \times \text{number of days ago}^6$ . Since the time period of our test is just the time of the pandemic, it is difficult to derive meaningful results from the momentum factor because the typical time period of 12 months is a third of our data. Additionally, since the basis of momentum is the calculation of returns, comparing cumulative returns of high and low momentum stocks is counterintuitive as high momentum stocks will inherently have higher returns.

One notable observation is that the top 5 highest momentum cryptocurrencies had generally small market caps which indicates high volatility.

### Volatility

Volatility was another factor that we explored, given its significance in the crypto markets, which are characterized by high levels of stochastic variance. We calculated daily volatility by taking the square root of the sum of the coin's opening price minus the price at N, divided by N, where N is the number of times we record the price of the coin during a single day. The coins were then split into high volatility and stability factors. This factor is particularly interesting to implement in the portfolio, given that cryptocurrencies are typically more volatile than traditional stocks. Being mindful of volatility could, therefore, lead to interesting results.

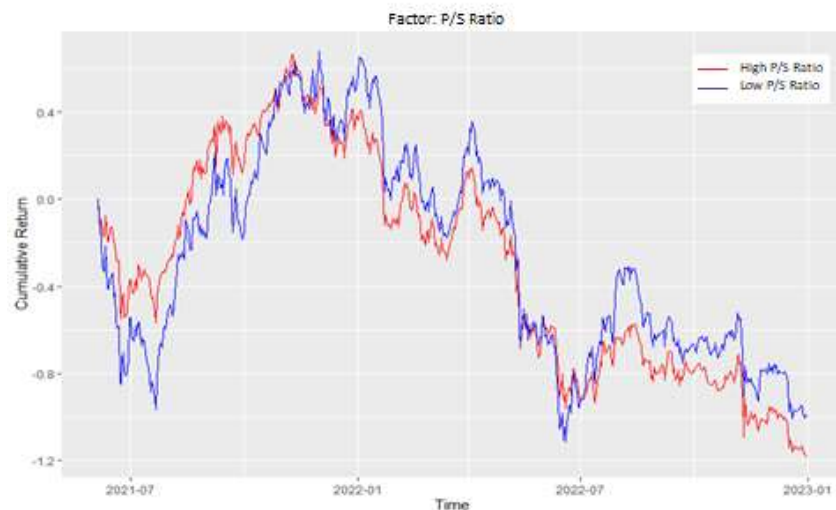
For our test, we took five cryptocurrencies out of the largest 100 market cap coins, three of them being the most volatile within the first three months of the pandemic and two being the most stable in this same time frame. The volatile coins were Bitcoin-cash, Dash, and Ethereum classic and the stable coins were Binance-usd and Dai. Then we graphed the cumulative return from March 2020 to March 2023 and noted that the volatile coins had large swings, but ultimately had much higher returns than the low volatility coins which did not have negative returns but stayed at nearly the same exact price during the whole pandemic.



**Figure 5.** Cumulative Return over time graph Volatility.

### P/S Ratio

We also considered the price to sales ratio (P/S Ratio), which is one factor that can be used in a cryptocurrency trading strategy. This ratio is calculated by taking the coin's fully diluted market cap and dividing it by its annualized revenues, where fully diluted market cap is the market cap of a cryptocurrency once all its coins are in circulation. We categorized cryptocurrencies by the top 5 and bottom 5 P/S Ratios out of the top 500 market cap coins. The low P/S ratio coins narrowly had higher returns than the high P/S coins but generally the cumulative returns stayed similar to each other during the entire time period. The P/S ratio factor does not seem like an effective portfolio strategy due to there not being a significant difference between portfolios with high and low ratios.



**Figure 6.** Cumulative Return over time graph by P/S Ratio.

*\*The observed time period started in June 2021 due to some of the low P/S ratio coins not being put into circulation until the middle of the pandemic.*

Overall, the application of factor investing to the crypto market is an exciting area of research that has significant potential for generating superior returns. By analyzing various factors such as market

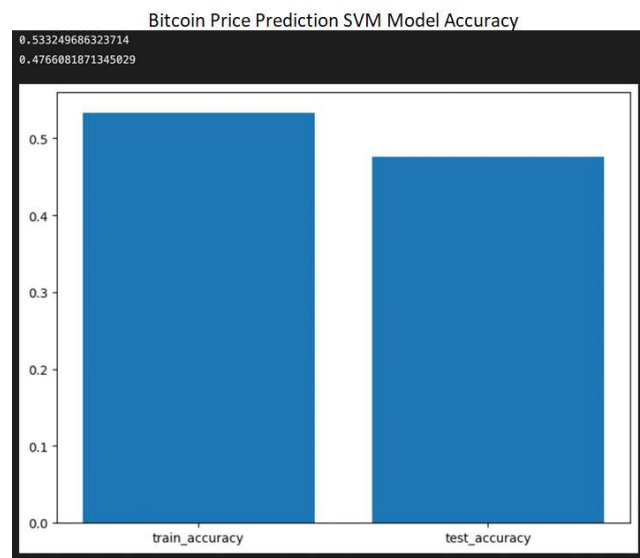
capitalization, value, momentum, volatility, and P/S ratio, we hope to provide valuable insights into the performance of the crypto market and enable investors to make better-informed investment decisions.

### Bitcoin Price Prediction

This paragraph outlines the final part of the project, which involves using machine learning models to predict the price of a chosen cryptocurrency. For this part of the project the goal was to expand the variables in our analysis and by doing so, try to predict the price of bitcoin. Due to time constraints, we were unable to implement the real-time data gathering process; Therefore, historical data for bitcoin was used in this analysis.

We first started by scaling the data to effectively standardize the machine learning operations. Then, we performed Principal Components Analysis to map out the most critical variables. Not surprisingly, the daily low and volume were deemed valuable in analyzing the closing price of Bitcoin.

The data was then split into a test and training data to follow up with Support Vector Machines on both sets. We chose SVM as it is a standard Machine Learning model for regression analysis. The predictor values were assigned as follows: price goes up = 1, price goes down = 0. The overall results were underwhelming as we only managed to attain a 53% accuracy on the training set and a 48% on the testing set. For the future, it would be interesting to test out different machine learning classifying techniques such as decision trees and linear regression and numerical predictions such as auto-regression and long-short term memory networks.



### LITERATURE SURVEY

#### Hedge and safe haven properties during COVID-19: Evidence from Bitcoin and gold<sup>2</sup>

We have conducted an empirical analysis of this paper on safe haven properties of Bitcoin and gold in comparison to various market indices. The results demonstrate the effectiveness of Bitcoin and gold as hedging assets in reducing the risk of international portfolios when applied to major world stock market indices and currencies. However, it is essential to note that the efficacy of Bitcoin and gold as safe havens may vary depending on the market conditions, such as the current COVID-19 pandemic. While gold is a weak safe haven during these times, Bitcoin's increased variability renders it unsuitable for



providing shelter in the current economic climate. The findings of this study have significant implications for investors who wish to minimize their risk exposure and optimize their portfolio performance.

### **Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic<sup>3</sup>**

As part of our research, we have conducted an analysis of this paper on the relationship between three cryptocurrencies, namely Bitcoin, Ethereum, and Tether, and equities. The study primarily focused on examining the downside risk reduction properties of these cryptocurrencies during the initial bear market period associated with the COVID-19 crisis. The empirical results suggest that Bitcoin and Ethereum do not, in general, act as safe havens for international equity markets. Instead, the researchers found evidence of increased downside risk for portfolios that consist of any allocation to these two assets, relative to holding the underlying equity index in isolation. In contrast, Tether is found to act as a safe haven. However, it was also observed that such downside risk hedging properties are not consistent over time due to large short-term historical losses in Tether. The findings imply that investors may need to exercise caution when considering cryptocurrency investments as part of their portfolio diversification strategy, and further research is needed to understand the underlying factors that contribute to the observed variations in downside risk reduction properties.

## **CONCLUSIONS**

### **Comparing Crypto returns vs Stock returns**

Our findings indicate that comparing crypto returns versus stock returns has yielded significant insights. Based on our analysis, we have reached a conclusion that during the global pandemic, crypto would have been a more profitable investment option than stocks. Although our sample size is limited, the results suggest that portfolios invested in crypto have demonstrated higher cumulative returns when compared to their stock counterparts.

### **"Factor" investing in Crypto**

Regarding "factor" investing in crypto, we have determined that constructing factor portfolios in the digital asset space is feasible and effective. Due to the unique nature of digital assets, some factors were more challenging to interpret, and we have had to identify comparable indices to guide our analysis. We calculated the indices for each asset and categorized them, allowing us to compare the performance of different factor categories and make informed investment suggestions. Each factor category showed differences in cumulative return performance. Considering the size, volume, supply, momentum, volatility, and P/S ratio of assets, investors can build their optimal crypto portfolios.

### **Bitcoin Price Prediction**

Finally, our hypothesis for bitcoin price prediction was that accurately forecasting the price of bitcoin is challenging, given the volatility of the crypto markets. Through this process, we aimed to identify potential opportunities for investors to optimize their returns while minimizing risks in the cryptocurrency market. The results obtained in this part of the project were underwhelming. However, if time permitted, it would have been of great value to evaluate different machine learning models especially the long-short-time long-short term memory networks as it offers robust unsupervised learning opportunities for models to track volatile assets such as cryptocurrencies.

### **Conclusion**

We aimed to comprehensively address all our research questions, providing deeper insights into the fundamental variables and factors at play in cryptocurrency investing. By doing so, we hoped to unlock novel approaches to maximizing investment returns by comparing and contrasting crypto and stock

portfolios. Our comprehensive analysis provides investors with an invaluable resource to make informed decisions on how to allocate their portfolios for optimal outcomes.

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