University of Lausanne
Hautes Études Commerciales (HEC)

Low Beta in Cryptocurrencies

For the Quantitative Asset & Risk Management II Class taught by Prof. Fabio Alessandrini

A project conducted and written by

Guillaume Pavé
guillaume.pave@unil.ch

Ruben Kempter
ruben.kempter@unil.ch

Dimitri André
dimitri.andre@unil.ch

Nicolas Eon Duval
nicolas.eonduval@unil.ch

UNIL | Université de Lausanne
HEC Lausanne

Abstract

This paper[1] explores volatility anomalies in the CAPM framework. We seek to explore Low Beta strategies in the cryptocurrencies world, to see if they exist and if so, if they present any interesting performance metrics. Our research led us to find and extract a High Beta anomaly in the cryptocurrency market. Interestingly, we extract the opposite effect than what can be found in traditional markets, such as equities, where a low beta anomaly can be observed. Different rebalancings (daily, weekly and monthly) are performed, and results do not diverge a lot from one rebalancing to another, showing the robustness of the strategies.

[1]You can find the Python implementation : Project Github

Contents

1 Introduction

Since the dawn of the financial markets, asset managers have been looking for the most profitable strategies which would bring in the highest returns for the lowest amount of risk involved. Numerous financial models have been created and expanded through in-depth research all around the world.

In the last couple of decades, financial researchers have discovered and dug into a market anomaly called low beta, a concept which exploits a false conception of the Capital Asset Pricing Model (CAPM), a pillar of the efficient market hypothesis. The CAPM links the expected return of an asset with its systematic risk through a coefficient named beta. This coefficient shows how the performance of an asset or a portfolio is linearly linked to the performance of a corresponding market portfolio.

When taking the beta of all the assets of a given market, the Security Market Line (SML) can be drawn. This positively sloped line shows that an asset with a higher beta will linearly receive more returns compared to the market portfolio, to compensate for the additional risk taken. In reality, research has proven that this line is flatter than what the CAPM predicts. This observation is the foundation of the low beta anomaly, which exploits the inaccuracy of the Security Market Line by going long on low beta assets and short on high beta assets.

A common explanation for this phenomenon resides in the non-normal distribution of returns, which in turn affects volatility. Including beta in the CAPM formula assumes that risk can be measured by a stock's price volatility. However, price movements in both directions are not equally risky. Using past data to determine a stock's volatility is not standard because stock returns and risk are not normally distributed. Thus, the low-volatility anomaly is based on the empirical phenomenon showing that stocks with lower risk earn a higher risk-adjusted return compared to higher risk stocks.

Additionally, many investors cannot use leverage, they are so-called constrained. Thus, when they want to increase their risk exposure, they can not borrow and pushed to invest in riskier equities, which subsequently have a higher beta.

This mechanism induces a pressure on the demand of high beta stocks and pushes their price up to the benefit of the low beta stocks, which experience lower demand. Consequently, the slope of the Security Market Line, which models the relationship between returns and betas, becomes less steep than predicted by the theory.

This observation has been extracted and disentangled in the equity market. In our project, we will be covering this anomaly in the cryptocurrency market, which has experienced tremendous growth over the past years.

Compared to other traditional financial assets, cryptocurrencies provide a new type of market which has its own advantages. This market has lower transaction fees and is open 24/7. Subsequently, these advantages have attracted the attention of an increasing number of financial investors to the crypto market in recent years. Numerous strategies have proven to be highly profitable, generating large returns. However, it is a highly volatile market and is subject to frequent speculative bubbles. Moreover, it is a rather new class of assets, which has been around for less than a decade. In May of 2020, the global market cap of the crypto market dropped from 2.66T (trillion) to 1.24T, a loss of more than 53 % in only 16 days. Hence, it is an asset class with major downside risk for investors. In other words, the cryptocurrency market is interesting for investors with low risk aversion.

This report will cover the Low Beta anomaly in the cryptocurrency market to see if it exists and, if it is the case, compare it to the same anomaly in the equity market.

2 Literature Review

Before diving into the core aspects of our report, it is necessary to go through the research that has already been done on the topic, which will provide further insights on the motivations behind our research.

The initial observations on the low-risk anomaly date back to Black et al. in 1972, who demonstrated experimentally using stock returns from 1926 to 1966 (Jensen et al., 1972). They found that predicted excess returns computed with CAPM on high-beta assets are lower than expected excess returns on low-beta, in the equity market. The same year, another study showed how low-beta equities outperformed on a similar period (1929-1971). In 2012, Asness et al. reported further evidence of a low-beta effect across asset classes (Asness et al., 2012), which gave birth to the famous "Betting against Beta" motto which was expanded into a factor, that has shown strong statistical significance across major asset classes, by Frazzini and Pedersen in 2014 (Frazzini and Pedersen, 2014).

Further research confirmed this low beta effect for other equity markets and Robeco researchers documented a similar low volatility effect (Blitz et al., 2014). They showed that lower volatility stocks generate higher risk-adjusted returns. In 2020, Zhu et al. used an advanced multi-factor model with algorithms which managed to show that the low volatility anomaly comes from the compensation of the risk of the underlying risk factors, which the Fama and French 5 factor model failed to extract and explain (Jarrow et al., 2021).

Since, the low-beta anomaly has been further researched in many papers, always leading to the same conclusion, which states that the Security Market Line is flatter than expected, and sometimes, it is even downward sloping, like shown by Han et al. in 2018, when looking at Chinese equities (Han et al., 2019).

When moving to the cryptocurrency world, such research is only starting giving the recent emergence of this class of assets. At the time of writing of this paper, previous studies on low beta and low volatility in the crypto world are close to none. One study conducted in 2020 on low volatility in cryptocurrencies did not show any significant findings on the matter (Burggraf and Rudolf, 2021). Later, authors of a new paper found that there are is only little difference in performance between naive diversification (1/N) and optimal diversification of Markowitz (Platanakis et al., 2018). Their study could be biased due to the small number of cryptocurrencies used, which were only 4.

In another paper, the researchers used daily data from twelve cryptocurrencies for over a period of three years. They identified the existence of a momentum effect, which was highly significant for short-term portfolios but disappeared over the longer-term (Panagiotis et al., 2020).

While factor analyses (Deng et al., 2019) have been implemented and momentum strategies (Rohrbach et al., 2017) have proof of existence in cryptocurrencies, only limited research has been done on the low beta and low volatility anomaly in this asset class.

Our research aims to bridge the gap between the world of cryptocurrencies and the low-beta anomaly, which has been observed in many other classes of assets, but has not been thoroughly documented in the cryptocurrency world, given the recent emergence of this asset class.

3 Data

3.1 Source

Our aim for this project was to find the most reliable source of data for cryptocurrencies historical prices. This can be difficult in an industry as uncertain and new as the cryptocurrency world. Several data sources involve schemes to get traders to invest in their project by manipulating data. Luckily, there are sources commonly trusted in the community. The first source for price data which is the most commonly used is CoinMarketCap, which lists all current tradable cryptocurrencies with more than 2000 listings at the time of writing. Any cryptocurrency which is tradable on any exchange with a price page can be listed on the website. This means that any cryptocurrency project can be listed on it with minimal working requirements. Since setting up a cryptocurrency does not have a high barrier to entry, a listing on CoinMarketCap does not represent a guarantee of project quality. Another data source found during our research was Santiment, which was founded by Maksim Balashevich in August 2016. This platform aims to improve data quality in the cryptocurrency space by making it beginner friendly and decentralized. They have created a token allowing to get premium access to data and which is also used as a reward for data contributors to the project. It also produces social sentiment data, hence the name of the project "Santiment". This platform provides an API for its users but has restrictions for its non-paying users. For this report, the data was fetched from the Santiment platform[2] as it is the easiest to use and the most complete we could find for a Python based program.

3.2 Configuration

A configuration file has been created to be able to make the code interactive. Users of the program can make changes to the following variables in the configuration file:

- $market\_cap$ = the minimum market capitalization a cryptocurrency has to achieve to be considered in the data selection (see 3.4.2).
- $number\_cryptos$ = the number of cryptocurrencies selected in the data preprocessing part.
- $windows$ = the number of days for the rolling volatilities calculations

After each change of the configuration variables, the preprocessing has to be run again for it to be taken into account in the strategies and results of the program.

3.3 Scraping

We used Sanpy[3], an open-source project under MIT license which provides easy to use functions to fetch data from the Santiment API. The data was fetched using a Python script with the following logic: first the slug of all cryptocurrencies was fetched with the $get(''project/all'').slug$ method and stored as a variable. Stablecoins names have been removed from this list as they are not relevant for the analysis. The list of stablecoins has been found on the Santiment website[4] and their matching slug was found on the graphical query interface. Once the list of stablecoins was removed from the overall cryptocurrency slugs, ohlc (open, high, low and close) and market capitalization data was fetched for each cryptocurrency in the resulting list. A maximum of 1000 rows could be fetched at each call therefore a further split of calls and

[2] https://dailybitcoinreport.com/what-is-santiment-net-san-beginners-guide/
[3] https://github.com/santiment/sanpy
[4] https://app.santiment.net/stablecoinsoverview

merging of resulting data had to be done. Each cryptocurrency was then stored in the raw folder as pickle files with the list of cryptocurrencies slugs stored as a binary.

3.4 Data Preprocessing

The data was preprocessed through three separate parts:

1. Market capitalization and close prices matrices creation
2. Date of appearence of cryptocurrencies and their market capitalization threshold
3. Creation of a returns matrix

The process is represented graphically in Figure 1.

3.4.1 Closing Prices and Market Caps

The goal of this first script is to merge individual cryptocurrency data into two matrices: the first one being the aggregate of the closing cryptocurrency prices and the second one representing the aggregate market capitalization for each cryptocurrency. To achieve this, each raw cryptocurrency file with ohlc and market capitalization data is fetched from the database. The closing prices and market capitalization are comprised in these raw files. Therefore, we split the data fetched and inputted the relevant data into the two objective matrices. Both matrices are then saved as CSV files in the database.

3.4.2 Cryptocurrency Selector

The cryptocurrency selector script has for goal to create two matrices: one with the list of cryptocurrencies and their corresponding date of first appearance in the data and a second one with the list of cryptocurrencies and their date of appearance for the first time the market capitalization of the cryptocurrency has reached the threshold in the configuration variable *market_ cap*. These matrices are created with the help of the raw ohlc and market capitalization data. Each one of these matrices is then stored in the database.

3.4.3 Returns Maker

The returns maker aims to provide a cleaned matrix of returns according to the configuration instructions. The market capitalization matrix created in the previous section 3.4.1 is fetched from the database and truncated with the number of cryptocurrencies indicated in the *number_ cryptos* configuration variable. Then, the most recent date is fetched from this matrix and subsequently used for filtering the closing price matrix created in section 3.4.1. The resulting truncated closing price matrix is reduced a second time by keeping only the cryptocurrencies which names are in the truncated market cap matrix mentioned above. The returns from this final matrix are calculated with the *pct_change*() method from the Pandas Python module. It is then stored as a CSV file in the database. Afterwards, a matrix of metrics is set up for following use in subsequent strategy scripts. Two replicas of the metrics matrix are created for the two rebalancing derivations for each strategy created further. These three files are saved in the database.

4 Methodology

4.1 Cap-Weighted Model

The Cap-Weighted strategy is made in the following way: first, the starting date of the portfolio is fetched from the database using the initial date where market capitalization exceeded the threshold from the *market_cap* configuration variable for all selected cryptocurrencies. Then, market capitalizations are fetched and filtered for the cryptocurrencies selected and the initial date. Afterwards, the sum of each row in the resulting matrix is calculated and added as the last column of the market capitalization matrix. The corresponding row sum is then used to divide each entry in each row. The last column representing the sum of each row is then dropped. This matrix therefore represents the weights used in the capitalization-weighted portfolio (see equation 1).

The returns from the selected cryptocurrencies are fetched and multiplied with this weight matrix in order to get the performance of the portfolio. A number of metrics are created at the end of the script using this performance matrix.

4.2 Equal-Weighted Model

The model is created using the returns from selected cryptocurrencies. The weights in this portfolio strategy are simply the returns from selected cryptocurrencies matrix where each input is replaced by $1/number\_cryptos$ (see equation 2). The resulting weights matrix is then used to compute portfolio performance by multiplying it with the returns from selected cryptocurrencies matrix.

Afterwards, this performance matrix is used to compute a number of metrics and different rebalancement strategies.

4.3 Minimum Variance Model

We computed a variance-covariance matrix for each date of our sample. Then, the weights have been optimized for minimum variance in the portfolio with a long-only constraint. Moreover, the full wealth has to be used meaning the sum of weights should be equal to 1. The optimization problem was then solved using the Sklearn Python Module resulting in a matrix of weights which was subsequently used to calculate the performance of the portfolio (see equation 3). These results and other metrics have been saved to the database.

4.4 Low-Beta Model

4.4.1 Different benchmarks

In this project we decided to work with 3 different benchmarks. The field is still at an experimental stage. That is why we chose to use different benchmarks as to improve the robustness of our analysis. The first benchmark we chose is the cap-weighted index as it is widely used in the equity market. The Bitcoin is prevalent in this index as its weight represents more than half of the total weight of the cap-weighted index. The second index was composed of the Bitcoin only. This choice was made because of its prevalence in media attention and its supposed high correlation with other cryptocurrencies. The third index used is an equally weighted index as to limit the impact of Bitcoin and see if a less concentrated index modified our results. In summary, we chose to use a cap-weighted index as in the equity market, an index composed only of Bitcoin and an equal-weighted index. These three indexes will serve as benchmarks.

4.4.2 Model

The logic of the model is the following: returns from the selected cryptocurrencies of the preprocessing part and benchmark returns are fetched from the database. Then, benchmark returns are added to the returns of the selected cryptocurrencies to form matrix A.

Matrix B is created as a shell for the betas. For each row of matrix A, betas corresponding to that row are calculated in the following way: data of matrix A up to that row index is used to create a variance-covariance matrix. The last column of that matrix represents the covariance of each cryptocurrency to the benchmark returns. As a reminder, the benchmark returns were added as the last column of matrix A. This column is then divided by the last entry in the column which represents the benchmark variance. This column is further used to fill in the corresponding row in the B matrix. The process is repeated until the matrix B is filled entirely. The last action is to cut the last column of this B matrix as it is filled with the beta of the benchmark.

Thereafter, two weights matrices, one for the Low Beta strategy and one for the High Beta strategy are created. There are two cases corresponding to different quantities of selected cryptocurrencies.

Case 1: the number of selected cryptocurrencies is lower than 20. A low weights matrix is created in the following way. The median of each row is calculated as a vector M. Then the B matrix is compared row by row to this median vector. The low weights matrix is set as $2/number\,of\,columns$ if the entry is lower or equal to the median and 0 otherwise. The process is repeated for the high weights but the zeros are replaced with $2/number\,of\,columns$ and vice-versa.

Case 2: the number of cryptocurrencies selected is higher than 20. The beta matrix is converted into quintiles for each row. The low weights matrix is created by converting the low quintile into $1/number\,of\,columns\,in\,the\,lowest\,quintile$. The other entries in the row are simply set to 0. The high weights matrix repeats the same process but replaces the highest quintile instead of the lowest.

These weights matrices are then used to calculate the returns of the Low Beta and High Beta strategies by multiplying the corresponding weights matrix to the returns matrix A. Then, the turnover and different rebalancement data are calculated with the help of these portfolio returns. They are subsequently saved to the database.

4.5 Low-Volatility Model

The low volatility model is created by fetching the selected cryptocurrencies returns from the database. The standard deviation with a rolling window as set in the in the *windows* configuration variable is calculated on this data set. This matrix of rolling volatilities is cleaned for non existing values. It is then used in the same way as in the previous section (4.4.2). The two cases are the same except that the matrix is not a beta matrix but a volatility matrix. The low volatility and high volatility weights are extracted in the same manner.

Then, these low and high volatility weights are multiplied with the selected cryptoccurency returns to create portfolio returns. The turnover and different rebalancement data are further calculated with the help of these portfolio returns. They are then saved to the database.

4.5.1 Leverage split

Another script is done on the low volatility strategy to split the data set into two parts. The split is done in February 2019. This date has been decided because it represents the launch of the Compound protocol which is the first major leverage exchange in the cryptocurrency industry allowing leverage. The methodology is the same as the low volatility model but the benchmark return dataset and the selected cryptocurrencies return dataset have been split into two distinct datasets. There is no change from the above section process other than it is repeated twice to account for the split.

4.6 Metrics functions

A number of functions have been implemented to calculate different metrics mentioned at the end of each model methodology in the above sections.

$getMonthlyTurnover(weights)$: The monthly turnover function goal is to return the turnover rate of the inputted weights by month. First, the difference between the weights matrix and the weights matrix shifted by one is summed over both axes. This creates the turnover over the whole period. The number of months is fetched from the index of the weights matrix using the numpy function timedelta. The turnover over the whole period is then divided by the number of months to create the output which represents the monthly turnover.

$createPortfolio7(weights, returns)$: The goal of this function is to create the portfolio returns on a weekly rebalancing basis. First, the row length of the weights index is fetched. Then, a range variable is created for each multiple of 7 starting from 0 to the length calculated above. This is then used to reduce the weights matrix with only indexes which are multiples of 7. The weights matrix is further expanded by repeating seven times each row. The resulting matrix is then multiplied with the returns matrix to get the rebalanced portfolio returns. The turnover is also calculated using the above function.

$createPortfolio30(weights, returns)$: This function works in the exact same manner as the $createportfolio7$ function. The only difference is that this function creates the portfolio for monthly rebalancement. Therefore the range calculated is a multiple of 30 instead of 7.

4.7 Metrics

Three matrices of metrics have been created in order to showcase our results. Each matrix represents a different rebalancement period for the portfolios (no rebalancement, 7 days, 30 days).

All of these metrics are calculated with a script fetching from the database of prices per strategy except for the turnover rate and the Herfindahl index which use weights as inputs and therefore could not be computed at the end with prices only. They are computed at the end of each strategy. A list of these metrics can be seen in Table 10.

5 Results

5.1 General results

First of all, it is important to mention the prevalence of Bitcoin in the market. Figure 2 and 3 show that the Bitcoin represents around 90% of the market in the portfolio of 20 cryptocurrencies and around 70% of the market in the portfolio of 100 cryptocurrencies. The market is still dominated by the Bitcoin at the moment. Therefore, the concentration in a traditional capitalization-weighted portfolio is very high. The Herfindahl-Hirschman Index for the Cap-Weighted strategy stumps its other competitors in Tables 1 and 2 seven-fold in almost all cases except for the Minimum-Variance portfolio.

The Table 3 shows a comparison of the different Sharpe ratios of strategies. The overall best strategy in terms of Sharpe ratio is the high volatility strategy with a portfolio of 100 cryptocurrencies at 4.31. The equal weighted strategies also have better Sharpe ratios than the average strategy. The other strategy that stands out is the High Beta with the equal weighted benchmark.

5.2 High Volatility anomaly

Regarding the analysis of a potential low volatility anomaly, the opposite is observed. In fact, we found that High Volatility portfolios outperform Low Volatility portfolios. This performance can be seen in Figure 5 and the different Sharpe ratios from Table 3. The Sharpe ratio difference between high volatility and low volatility strategies goes from 0.48 to 1.09 with 20-cryptocurrencies portfolio and 0.07 to 4.31 with 100-cryptocurrencies portfolio. The gap widens when taking into account more cryptocurrencies. This could be explained by the construction of our model since the 20-cryptocurrencies portfolio uses the median to separate between high and low volatility cryptocurrencies and the 100-cryptocurrencies portfolio uses the 1st and last quintile to create the different portfolios therefore increasing the effect. An increase of the effect when taking into account only the more volatile cryptocurrencies would suggest the existence of a high volatility anomaly. This overperformance can also be potentially explained by the fact that highly volatile cryptocurrencies are less liquid as Figure 9 shows.

5.3 High Beta anomaly

From our calculations, we can see a trend towards a High Beta outperformance. It can be seen in Figure 4 and in the Sharpe ratios from Table 3. The High Beta strategies overperform their Low Beta counterparts in all cases with portfolios of 100 cryptocurrencies. The difference of Sharpe ratio is of 0.14 with capitalization-weighted benchmark, 0.07 with the Bitcoin benchmark and 2.73 with the Equal-Weighted benchmark. The anomaly is not present for the 20 cryptocurrencies portfolio except for strategies using the equal weighted benchmark. This may be due to our methodology since we used the highest and lowest quintile for the portfolio of 100 cryptocurrencies but the median as a separator for the 20 cryptocurrencies portfolio. Therefore, the Low and High beta strategies with 20 cryptocurrencies portfolio are closer to a market portfolio than their 100 cryptocurrencies counterparts.

These results suggest that the outperformance could be explained by the highly volatile cryptocurrencies at the end of the spectrum. Indeed, cryptocurrencies with a volatility relatively close to the market portfolio are underperforming in our sample and weigh down on the overall strategy performance. The 20 cryptocurrencies Low Beta portfolio with equal weighted portfolio as benchmark does not suffer from the same issue of a reversal of the High Beta anomaly. This could be due to the fact that since most cryptocurrencies have a higher volatility than Bitcoin, it biases the High Beta portfolio with equal weighted benchmark to a higher volatility. Indeed, this can be seen by comparing the volatility of the High Beta strategies by benchmark in Tables 1 and 2. The High Beta equal-weighted is 2% more volatile than its counterparts in the 20 cryptocurrencies portfolio and the difference gets to a maximum of 31% in the case of the 100 cryptocurrencies portfolios. These results suggest that the outperformance comes from the highest beta cryptocurrencies.

6 Sensitivity analysis

6.1 Low volatility split for leverage

In order to determine whether access to leverage had an influence on the anomaly, we decided to separate our sample into two parts, before and after February 2019, when the Compound protocol allowing leverage was made available. Regarding the portfolio of 20 cryptos, there was no big change in the anomaly between before and after the leverage access, which reflects the fact that these cryptos have close to market behavior, and that few of them have extreme profiles. However, when we expand our universe to 100 cryptos, we realize that the Sharpe ratio of high volatilities is skyrocketing to 5.83. The difference in Sharpe ratio between High Beta minus Low Beta goes from 0.79 before February 2019 to 5.45 after, further reinforcing and amplifying our High Beta anomaly. Full results can be seen in Table 13 and 14.

We believe that access to leverage has allowed crypto investors, who have a strong attraction to risk, to use their leverage to invest even more massively in volatile cryptos. The daily rebalancing as well as the huge Sharpe ratios indicate that investors are taking advantage of the leverage to create pump and dumps and try to gain huge returns in a very short period of time. Cryptocurrency investors are massively pushed by cryptocurrency brokers (such as Binance or Coinbase) to use margin accounts.

6.2 Different rebalancement periods

We also tested different rebalancement periods for the portfolios. We created two different rebalancement periods, one each 7 days (weekly) and one each 30 days (monthy). Full results can be found under Tables 6, 7, 8 and 9.

First of all, in terms of performance, we can see that rebalancing has a small negative impact on the Capitalization-weighted portfolio. This could be the result of reducing positions quickly in cryptocurrencies which fall in market capitalization as opposed to rebalancing every 30 days where the weighting shift is slower.

Regarding the high volatility anomaly, we can see a decrease in performance when the rebalancing frequency is reduced to weekly and monthly rebalancing. The high volatility Sharpe ratio of 4.31 for the 100 cryptocurrencies portfolio drops down to 3.84 when rebalancing each 7 days and further down to 2.81 when rebalancing each 30 days. This would suggest that the overperformance in the High Volatility portfolio is best captured with a daily rebalancing portfolio. Also, it would mean that highly volatile cryptocurrencies are only profitable when they are at the top of their volatility. Once they become less volatile, investors' interest drops in favor of other more highly volatile cryptocurrencies decreasing the profitability of the former.

For the Low Beta strategies, we found that the 7-day rebalancement inverses the relationship between Low and High Beta. With 30-days rebalancement, the effect is decreased but the High Beta still outperforms the Low Beta with a smaller delta. The Low Beta strategies use the volatility factor a lot and since the high volatility strategy loses a lot of performance with longer rebalancement periods, this also impacts the Low Beta strategies to the point of a reversal for the 7-days rebalancement period. The effect of rebalancing on a 7-days basis has a larger impact than when we switch to a 30-days basis, on the monthly returns. This could be due to the fact that cryptocurrencies investors who buy highly volatile cryptocurrencies do not hold them for more than a few days and therefore create a crash following the pump. Our 7-days rebalancing portfolio would be catching this effect.

7 Conclusion

The general idea of our paper was to uncover the smart beta effect in the cryptocurrency world, this effect having already been extracted in other asset classes such as equities. Instead of extracting a Low Beta anomaly, we managed to identify a High Beta and a High Volatility effect, which can be used to create highly profitable portfolios with attractive risk-reward aspects. In the cryptocurrencies world, the Security Market Line is in fact steeper than what the CAPM predicts. We further expanded our research to a larger basket of cryptocurrencies, going from 20 to 100 individual assets, and this expansion has shown even more impressive performances.

Cryptocurrencies have gathered massive public attention in the past years and will probably continue to grow in the years to come. Volatility is the most interesting aspect of this asset class and investors of all kinds will continue to speculate on the large moves around the drift.

7.1 Recommendation

Based on the arguments given above, we would only recommend investing in our cryptocurrency portfolios to clients with low risk aversion. The impressive excess returns generated by our portfolio come at the cost of a higher volatility than what is usually found in other asset classes. Risk averse investors should invest in our portfolios only for diversification purposes. Smart beta portfolios in equities for instance offer much lower Sharpe ratios that our portfolios and this effect is due to the lower volatility that can be found in equities.

For a risk-seeking investor, we would recommend investing in a portfolio with a high Sharpe Ratio for to maximize risk-return taken and with the lowest turnover, to reduce the costs of transaction, although these are often quite low when investing in cryptocurrencies. The High Beta Equally Weighted portfolio offers the best performance based on the risk-return and turnover criteria, in both the 20 and 100 cryptocurrencies baskets.

Smart beta portfolios in the cryptocurrency world offer great opportunities to risk-seeking investors. We would highly recommend investing in different portfolios, which offer a broad range of possibilities when looking at Sharpe ratios, maximum drawdowns, volatilities and turnovers.

7.2 Limitations

While our project brings interesting in-depth insights into the smart beta world of cryptocurrencies, further developments could include creating dynamic strategies or adding different frequencies of rebalancing.

Furthermore, a major limitation of our portfolios is liquidity. Indeed, when expanding to 100 cryptocurrencies, liquidity decreases, with positions being taken in some cryptocurrencies with low volume and large bid-ask spreads. As mentioned before, there is a negative correlation between liquidity and volatility. Further research can be made to better understand this liquidity issue. Other constraints could be added such as a minimum daily volume threshold.

Regarding the High Beta anomaly, further research to pinpoint at which percentage of the beta spectrum the outperformance materializes would be needed.

List of Figures

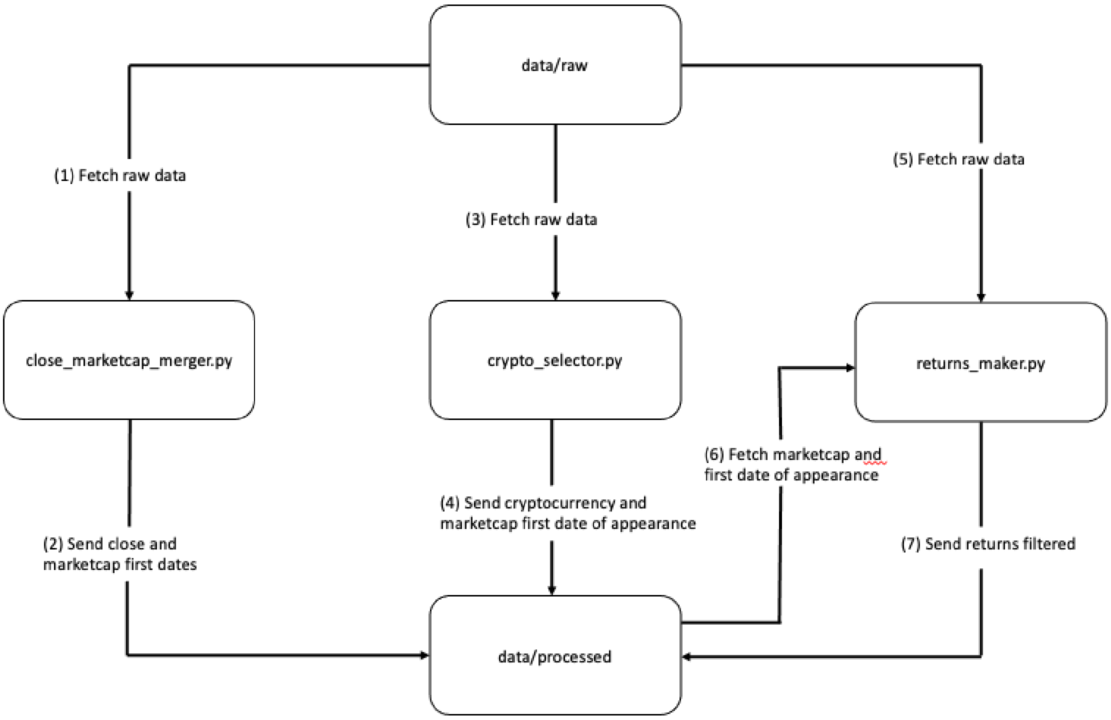

Figure 1: Data processing

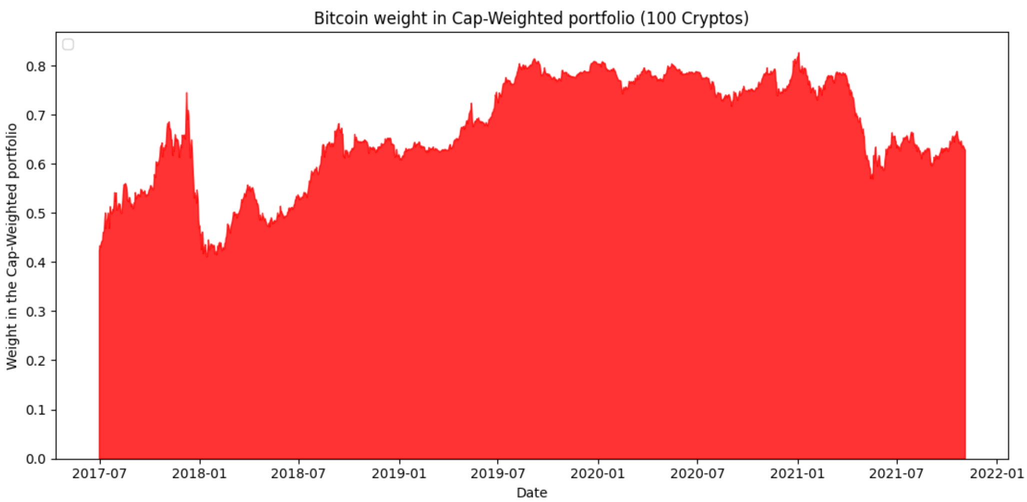

Figure 2: Bitcoin weight in market portfolio (100 cryptos)

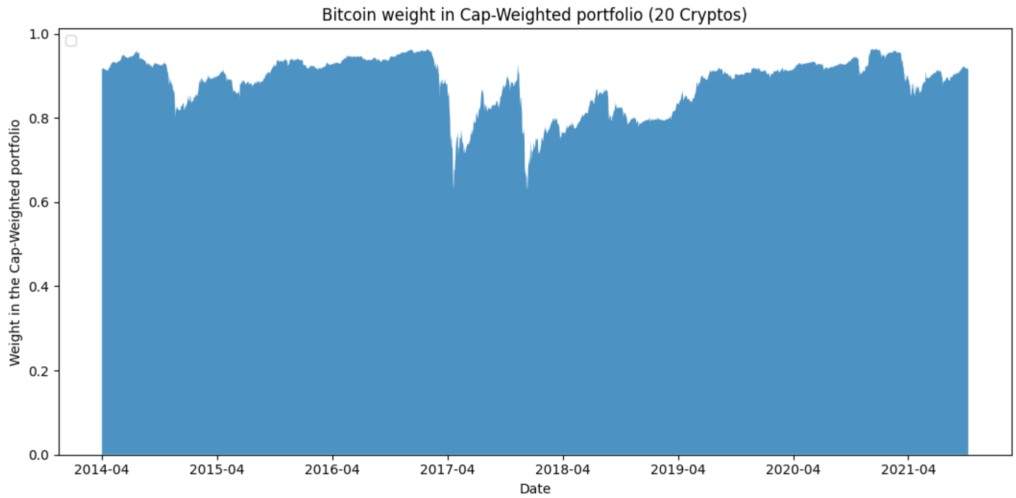

Figure 3: Bitcoin weight in market portfolio (20 cryptos)

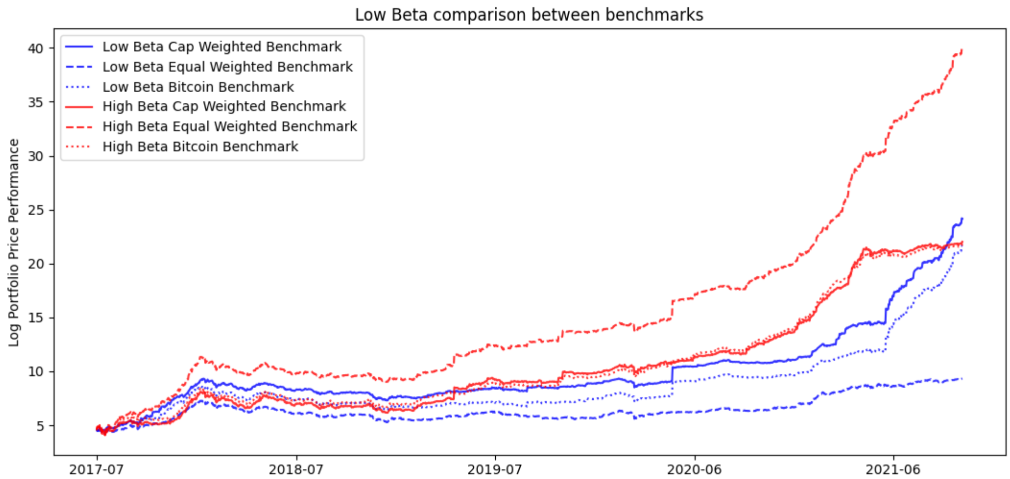

Figure 4: Comparison of different low beta strategies for 100 cryptocurrencies portfolio

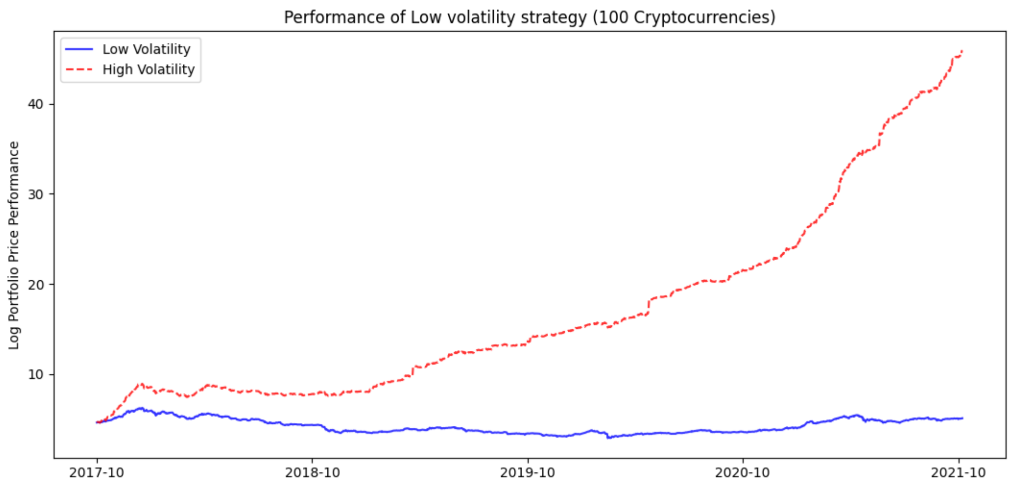

Figure 5: Performance of High volatility vs Low volatility portfolio (100 cryptocurrencies)

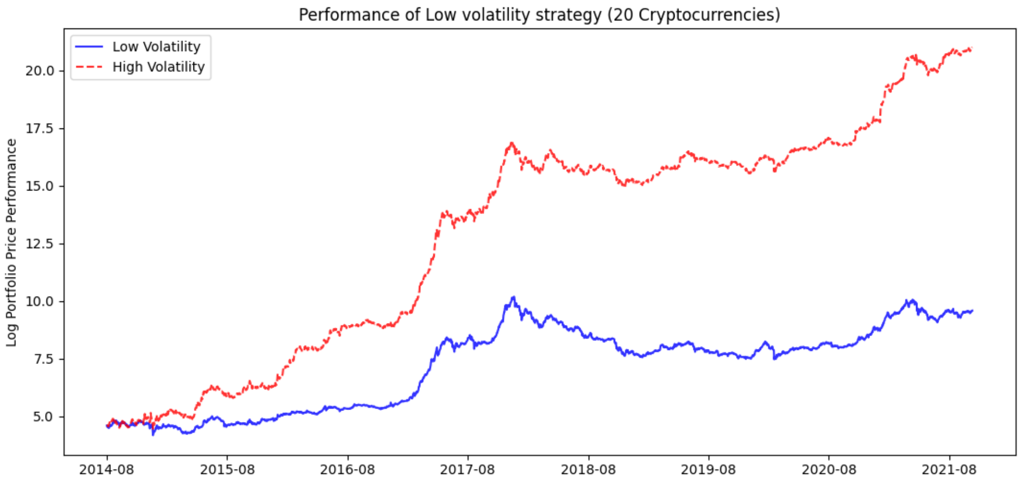

Figure 6: Performance of High volatility vs Low volatility portfolio (20 cryptocurrencies)

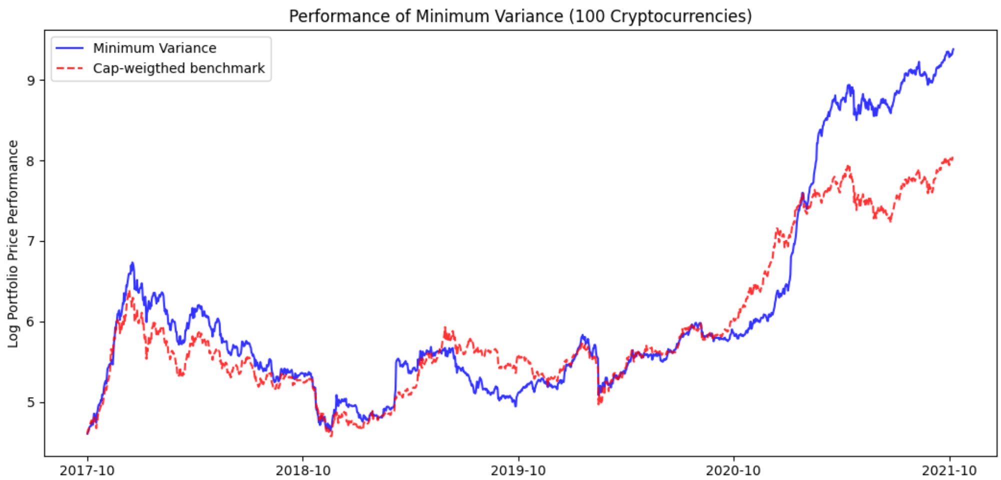

Figure 7: Minimum Variance portfolio vs Cap-weigthed benchmark (100 cryptocurrencies)

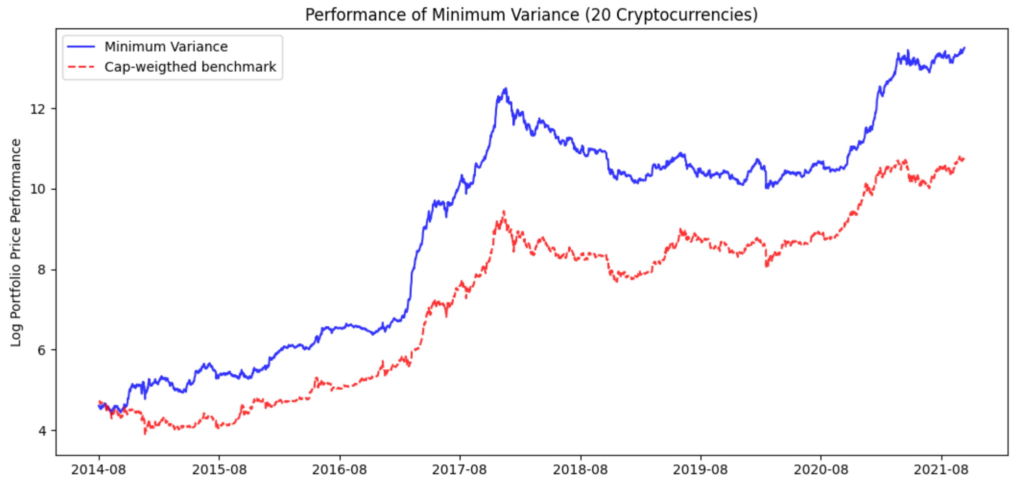

Figure 8: Minimum Variance portfolio vs Cap-weigthed benchmark (20 cryptocurrencies)

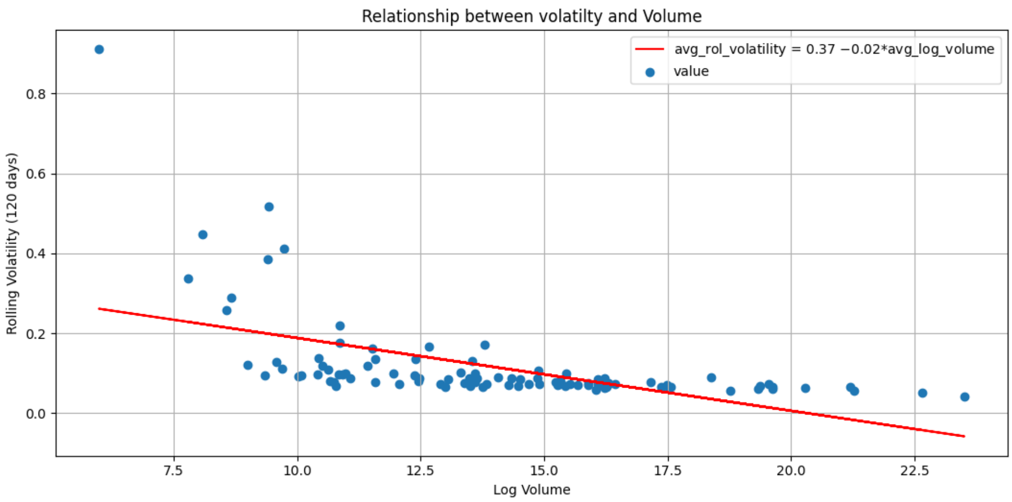

Figure 9: Relationship between Volume and Volatility (100 cryptocurrencies)

List of Tables

Table 1: Metrics for each strategy with 20 cryptocurrencies

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover	HHI
CW	0.11	0.21	0.51	0.00	1.00	-0.35	0.00	NaN	0.20	7941.00
BTC	0.09	0.21	0.41	-0.02	0.97	-0.36	0.01	-122.10	0.00	1.00
EW	0.22	0.24	0.90	0.11***	0.92	-0.42	0.03	187.31	0.00	500.00
MV	0.16	0.21	0.76	0.05*	0.80	-0.40	0.03	82.61	3.46	1799.00
Low Vol	0.10	0.22	0.48	-0.00	0.87	-0.45	0.02	-49.77	0.76	1000.00
High Vol	0.35	0.32	1.09	0.24***	0.96	-0.38	0.05	264.88	0.76	1000.00
Low Beta	0.20	0.24	0.80	0.09**	0.82	-0.41	0.03	112.20	0.47	1000.00
High Beta	0.23	0.29	0.80	0.13***	1.02	-0.42	0.04	187.18	0.47	1000.00
Low Beta EW	0.13	0.22	0.57	0.02	0.81	-0.42	0.02	18.13	0.21	1000.00
High Beta EW	0.31	0.31	1.01	0.21***	1.19	-0.42	0.05	230.58	0.21	1000.00
Low Beta BTC	0.20	0.25	0.82	0.10**	0.76	-0.46	0.03	128.86	0.52	1000.00
High Beta BTC	0.23	0.29	0.78	0.12***	0.97	-0.40	0.04	172.47	0.52	1000.00

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Metrics for each strategy with 100 cryptocurrencies

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover	HHI
CW	0.07	0.22	0.30	0.00	1.00	-0.40	0.00	NaN	0.39	4944.00
BTC	0.06	0.21	0.27	-0.01	0.93	-0.36	0.01	-48.02	0.00	1.00
EW	0.32	0.29	1.10	0.25***	0.99	-0.44	0.04	224.51	0.00	100.00
MV	0.12	0.23	0.53	0.05	0.77	-0.43	0.03	33.73	4.41	939.00
Low Vol	0.02	0.23	0.07	-0.05**	0.94	-0.47	0.02	-163.97	1.66	500.00
High Vol	3.14	0.73	4.31	3.07***	1.00	-0.42	0.16	285.03	0.83	500.00
Low Beta	0.73	0.50	1.47	0.66**	0.69	-0.40	0.13	140.91	0.66	500.00
High Beta	0.79	0.49	1.61	0.72**	1.26	-0.49	0.08	193.53	0.61	500.00
Low Beta EW	0.09	0.23	0.38	0.02	0.54	-0.44	0.02	17.35	0.38	500.00
High Beta EW	2.24	0.72	3.10	2.17**	2.42	-0.51	0.16	234.78	0.51	500.00
Low Beta BTC	0.67	0.48	1.39	0.60**	0.65	-0.44	0.13	127.58	0.64	500.00
High Beta BTC	0.60	0.41	1.46	0.53***	1.19	-0.46	0.06	245.27	0.72	500.00

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Sharpe Ratios of strategies adjusted for turnover

	CW	BTC	EW	MV	Low Vol	High Vol	Low Beta	High Beta	Low Beta EW	High Beta EW	Low Beta BTC	High Beta BTC
Sharpe 20 adjusted	0.51	0.41	0.90	0.71	0.47	1.08	0.80	0.79	0.56	1.01	0.81	0.77
Sharpe 100 adjusted	0.30	0.27	1.10	0.47	0.04	4.31	1.46	1.60	0.37	3.10	1.38	1.45

Table 4: Sharpe Ratio of strategies adjusted for turnover (Rebalanced 7 days)

	CW	BTC	EW	MV	Low Vol	High Vol	Low Beta	High Beta	Low Beta EW	High Beta EW	Low Beta BTC	High Beta BTC
Sharpe 20 rebalanced 7 adjusted	0.42	0.41	0.90	0.73	0.66	0.91	0.82	0.77	0.83	0.77	0.82	0.77
Sharpe 100 rebalanced 7 adjusted	0.24	0.27	1.10	0.45	0.20	3.84	1.54	1.32	1.54	1.32	1.31	1.44

Table 5: Sharpe Ratio of strategies adjusted for turnover (Rebalanced 30 days)

	CW	BTC	EW	MV	Low Vol	High Vol	Low Beta	High Beta	Low Beta EW	High Beta EW	Low Beta BTC	High Beta BTC
Sharpe 20 rebalanced 30 adjusted	0.40	0.41	0.90	0.73	0.67	0.91	0.80	0.79	0.80	0.79	0.85	0.75
Sharpe 100 rebalanced 30 adjusted	0.23	0.27	1.10	0.99	0.25	2.81	1.34	1.70	1.34	1.70	1.41	1.69

Table 6: Metrics for each strategy with 20 cryptocurrencies (Rebalanced 7 days)

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover
CW	0.09	0.20	0.42	0.00	1.00	-0.35	0.00	NaN	0.09
BTC	0.09	0.21	0.41	-0.00	0.99	-0.36	0.01	15.87	0.00
EW	0.22	0.24	0.90	0.13**	0.92	-0.42	0.03	225.01	0.00
MV	0.16	0.22	0.75	0.07**	0.82	-0.41	0.03	124.37	1.00
Low Vol	0.15	0.23	0.66	0.06*	0.91	-0.46	0.03	98.17	0.44
High Vol	0.28	0.31	0.92	0.19***	0.93	-0.38	0.04	239.77	0.44
Low Beta	0.21	0.25	0.83	0.12***	0.87	-0.42	0.03	176.41	0.27
High Beta	0.22	0.28	0.77	0.13***	0.97	-0.41	0.04	189.80	0.27
Low Beta EW	0.21	0.25	0.83	0.12***	0.94	-0.42	0.03	176.41	0.09
High Beta EW	0.22	0.28	0.77	0.13***	1.06	-0.41	0.04	189.80	0.09
Low Beta BTC	0.21	0.25	0.82	0.12***	0.80	-0.46	0.03	174.15	0.27
High Beta BTC	0.22	0.28	0.78	0.13***	0.93	-0.40	0.04	193.71	0.27

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Metrics for each strategy with 100 cryptocurrencies (Rebalanced 7 days)

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover
CW	0.05	0.22	0.24	0.00	1.00	-0.41	0.00	NaN	0.16
BTC	0.06	0.21	0.27	0.00	0.94	-0.36	0.01	19.19	0.00
EW	0.32	0.29	1.10	0.26***	0.99	-0.44	0.04	237.92	0.00
MV	0.10	0.22	0.47	0.05	0.79	-0.42	0.03	44.28	1.46
Low Vol	0.05	0.24	0.21	-0.00	0.97	-0.47	0.02	-35.71	0.85
High Vol	2.73	0.71	3.84	2.68***	0.92	-0.42	0.16	265.86	0.52
Low Beta	0.61	0.40	1.54	0.56***	0.88	-0.41	0.10	177.27	0.32
High Beta	0.65	0.49	1.32	0.59***	1.05	-0.47	0.10	164.58	0.32
Low Beta EW	0.61	0.40	1.54	0.56***	1.16	-0.41	0.10	177.27	0.20
High Beta EW	0.65	0.49	1.32	0.59***	1.36	-0.47	0.10	164.58	0.23
Low Beta BTC	0.40	0.30	1.32	0.34**	0.85	-0.43	0.07	158.73	0.32
High Beta BTC	0.71	0.49	1.45	0.66***	1.02	-0.44	0.10	176.18	0.37

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Metrics for each strategy with 20 cryptocurrencies (Rebalanced 30 days)

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover
CW	0.08	0.20	0.40	0.00	1.00	-0.36	0.00	NaN	0.05
BTC	0.09	0.21	0.41	0.00	1.00	-0.36	0.01	69.51	0.00
EW	0.22	0.24	0.90	0.14**	0.92	-0.42	0.03	233.54	0.00
MV	0.16	0.22	0.74	0.08**	0.81	-0.39	0.03	136.95	0.50
Low Vol	0.16	0.24	0.67	0.08**	0.92	-0.45	0.03	116.63	0.27
High Vol	0.27	0.30	0.91	0.19***	0.91	-0.38	0.04	243.13	0.27
Low Beta	0.20	0.25	0.80	0.12***	0.88	-0.41	0.04	174.73	0.13
High Beta	0.23	0.28	0.79	0.14***	0.96	-0.42	0.04	204.22	0.13
Low Beta EW	0.20	0.25	0.80	0.12***	0.95	-0.41	0.04	174.73	0.06
High Beta EW	0.23	0.28	0.79	0.14***	1.05	-0.42	0.04	204.22	0.06
Low Beta BTC	0.22	0.25	0.85	0.13***	0.81	-0.47	0.04	187.37	0.12
High Beta BTC	0.21	0.28	0.75	0.13***	0.92	-0.38	0.04	195.22	0.12

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Metrics for each strategy with 100 cryptocurrencies (Rebalanced 30 days)

	monthly_returns	volatility	sharpe	excReturns	beta	max_drawdown	TE	IR	monthly_turnover
CW	0.05	0.22	0.23	0.00	1.00	-0.42	0.00	NaN	0.09
BTC	0.06	0.21	0.27	0.01	0.94	-0.36	0.01	34.32	0.00
EW	0.32	0.29	1.10	0.26***	0.99	-0.44	0.04	241.92	0.00
MV	0.25	0.25	1.00	0.20	0.81	-0.41	0.04	88.15	0.69
Low Vol	0.06	0.24	0.26	0.01	0.97	-0.46	0.02	1.30	0.50
High Vol	1.97	0.70	2.82	1.91***	0.94	-0.43	0.16	250.48	0.36
Low Beta	0.51	0.38	1.34	0.46**	0.95	-0.42	0.09	160.29	0.18
High Beta	0.83	0.49	1.70	0.78**	0.99	-0.48	0.10	167.15	0.16
Low Beta EW	0.51	0.38	1.34	0.46**	1.15	-0.42	0.09	160.29	0.12
High Beta EW	0.83	0.49	1.70	0.78**	1.35	-0.48	0.10	167.15	0.12
Low Beta BTC	0.44	0.31	1.41	0.38**	0.93	-0.43	0.07	157.84	0.17
High Beta BTC	0.83	0.49	1.69	0.78**	0.96	-0.44	0.10	178.86	0.19

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Metrics list

Variable	**Meaning**
monthly_returns	Average monthly returns of the portfolio strategy
volatility	Average monthly volatility of the portfolio strategy
sharpe	sharpe ratio of the strategy
excReturns	Average monthly excess returns
beta	Beta of the portfolio strategy compared to the corresponding benchmark
max_drawdown	Maximum monthly returns drawdown of the strategy
TE	Tracking error with the corresponding benchmark portfolio
IR	Information ratio with the corresponding benchmark
monthly_turnover	Monthly turnover
HHI	Herfindhal-Hirschman index for the weights in the portfolio

Table 11: Excess returns t-stat and sharpe significance 20 cryptocurrencies

	cap_weighted_index	BTC	equally_index	MV	LV	HV	LB	HB	LB_EW	HB_EW	LB_BTC	HB_BTC
Sharpe ratio p-value	0.271635	0.176028	0.641396	0.507883	0.237933	0.823280	0.544422	0.542210	0.322570	0.743576	0.561935	0.524433
Sharpe ratio p-value reb7	0.186015	0.176028	0.641396	0.493957	0.414017	0.656918	0.570698	0.513464	0.570698	0.513464	0.563460	0.520921
Sharpe ratio p-value reb30	0.164263	0.176028	0.641396	0.485191	0.418580	0.651328	0.540720	0.536929	0.540720	0.536929	0.588871	0.499205
Excess returns p-value	None	0.084695	0.002585	0.084694	0.886211	0.000213	0.015813	0.001893	0.385320	0.000557	0.011123	0.002530
Excess returns p-value reb7	None	0.827424	0.001658	0.032111	0.057905	0.000300	0.003216	0.002789	0.003216	0.002789	0.004849	0.001728
Excess returns p-value reb30	None	0.457606	0.001652	0.027357	0.043908	0.000291	0.003702	0.002397	0.003702	0.002397	0.004654	0.001755

Table 12: Excess returns t-stat and sharpe significance 100 cryptocurrencies

	cap_weighted_index	BTC	equally_index	MV	LV	HV	LB	HB	LB_EW	HB_EW	LB_BTC	HB_BTC
Sharpe ratio p-value	-0.01334	-0.048168	0.735923	0.198098	-0.234971	3.784205	1.077981	1.210834	0.055064	2.630795	1.003744	1.070048
Sharpe ratio p-value reb7	-0.072917	-0.048168	0.735923	0.137997	-0.098166	3.336129	1.146133	0.938531	1.146133	0.938531	0.937416	1.058216
Sharpe ratio p-value reb30	-0.08493	-0.048168	0.735923	0.639097	-0.058489	2.358403	0.956657	1.301731	0.956657	1.301731	1.022942	1.287215
Excess returns p-value	None	0.312341	0.001001	0.290616	0.011474	0.008870	0.022683	0.023025	0.481237	0.015002	0.042895	0.000529
Excess returns p-value reb7	None	0.703069	0.000600	0.237079	0.903855	0.008793	0.004988	0.002310	0.004988	0.002310	0.018873	0.002233
Excess returns p-value reb30	None	0.491976	0.000550	0.223442	0.657271	0.001973	0.011493	0.042653	0.011493	0.042653	0.031908	0.023347

Table 13: Low volatility metrics based on split on 2019-02-01 (20 cryptocurrencies)

	monthly_returns	volatility	sharpe	excess_returns
Low Vol Before	0.125833	0.216868	0.570223	0.031095
High Vol Before	0.403986	0.334584	1.200945	0.309248
Low Vol After	0.099117	0.217415	0.44988	-0.008293
High Vol After	0.316663	0.296329	1.06421	0.209253

Table 14: Low volatility metrics based on split on 2019-02-01 (100 cryptocurrencies)

	monthly_returns	volatility	sharpe	excess_returns
Low Vol Before	-0.141508	0.269196	-0.533731	-0.259186
High Vol Before	0.09949	0.373624	0.260477	-0.018187
Low Vol After	0.09317	0.2168	0.423726	-0.025503
High Vol After	5.226918	0.889815	5.872695	5.108245

Bibliography

Asness, C. S., Frazzini, A., and Pedersen, L. H. (2012). Leverage aversion and risk parity. v. 68(1):pp. 47–59.

Blitz, D., Falkenstein, E., and van Vliet, P. (2014). Explanations for the volatility effect: An overview based on the CAPM assumptions. page pp. 18.

Burggraf, T. and Rudolf, M. (2021). Cryptocurrencies and the low volatility anomaly. v. 40:pp. 101.

Deng, X., Chuen, Y., Wang, X., and Zhang (2019). A five factor cryptocurrency pricing model.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. v. 111(1):pp. 1–25.

Han, X., Li, K., and Li, Y. (2019). Investor overconfidence and the security market line: New evidence from china. page pp. 44.

Jarrow, R. A., Murataj, R., Wells, M. T., and Zhu, L. (2021). The low-volatility anomaly and the adaptive multi-factor model.

Jensen, M. C., Black, F., and Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests.

Panagiotis, T., Renatas, K., and Bayasgalan, T.-A. (2020). Momentum trading in cryptocurrencies: Short-term returns and diversification benefits. v. 191:pp. 108.

Platanakis, E., Sutcliffe, C., and Urquhart, A. (2018). Optimal vs naïve diversification in cryptocurrencies. v. 171:pp. 93–96.

Rohrbach, J., Suremann, S., and Osterrieder, J. (2017). Momentum and trend following trading strategies for currencies and bitcoin. page pp. 22.

Appendix

A Weighting Schemes

A1 Cap-weighted benchmark

For the cap-weighted benchmark, weights are computed with the following formula:

$$w_{it} = \frac{Marketcap_{it}}{\sum_{j=1}^{N} Marketcap_{jt}} \tag{1}$$

A2 Equally-weighted benchmark

For the equally-weighted benchmark, weights are computed with the following formula:

$$w_{it} = \frac{1}{N} \tag{2}$$

where N: number of cryptocurrencies

A3 Minimum variance

For the minimum variance portfolio, weights are computed thanks to the following optimization problem:

$$\begin{aligned} \min_{w} \quad & w' \sum w \\ \text{s.t.} \quad & 1w' = 1 \\ & w_{it} \geq 0 \end{aligned} \tag{3}$$