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A re-study of Parma and Wassvik

Does Parma and Wassvik's conclusion of "Should a well-diversified portfolio contain cryptocurrencies?" from the period 2010-2017 hold true when compared to the period 2017-2022 using similar data?

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Abstract

This study reevaluates the conclusions of Parma and Wassvik's thesis, which examined the performance of cryptocurrencies as investments from 2010 to 2017. The objective was to determine whether cryptocurrencies remain a profitable investment opportunity in the subsequent period from 2017 to 2022 and their suitability for inclusion in a diversified portfolio, considering the significant volatility in the crypto market in recent years. In addition, we constructed our own portfolio to reflect the average benchmark of crypto investors, as not all investors have access to the MSCI International World Price Index used in Parma and Wassvik.

Upon analyzing the data, we find that the original thesis's conclusion still holds true. While cryptocurrencies, particularly Ethereum and Bitcoin, have demonstrated the potential for higher returns compared to traditional assets, their performance has diminished during the 2017-2022 period. Although the variance has decreased, indicating lower volatility, the significant decrease in returns has impacted the overall performance. This can be attributed to the high and constant weekly price growth observed in cryptocurrencies from 2010 to 2017, which resulted in high variance and average returns. In contrast, the 2017-2022 period witnessed both negative and positive price changes with less extreme observations, leading to lower returns and lower variance.

Despite the decrease in risk and return compared to Parma and Wassvik's findings, cryptocurrencies still offer potential benefits when considering the risk-return tradeoff. However, their performance metrics do not surpass those of the previous period. It is worth noting that the data used in Parma and Wassvik's study were influenced by extreme positive observations (outliers), such as the rapid increase in crypto prices in 2017. In our study, we capture both dramatic price increases and decreases, resulting in fewer outliers and more reliable data with more conclusive metrics, affirming that cryptocurrencies outperform all assets despite their variance.

In conclusion, our study with new and more reliable data confirms that cryptocurrencies should be included in a well-diversified portfolio and have demonstrated superior investment potential compared to alternative assets available in our dataset. Cryptocurrencies have also proven to be a favorable investment compared to the market portfolio constructed to represent the average investment opportunity for crypto investors However, it is crucial to acknowledge that our research focused on the period from 2017 to 2022, and further investigations should continue to monitor the long-term investment performance of cryptocurrencies for a comprehensive understanding of their potential.

Preface

This assignment marks the culmination of a two-year Master's degree in Economics and Business Administration at OsloMet.

The aim of this thesis is to reevaluate Parma and Wassviks findings that a well-diversified portfolio should include cryptocurrencies with a quantitative perspective using newer data. Our research question is both interesting and current as cryptocurrencies has been a hot topic in recent years.

We became interested in our topic after a significant decrease in the prices of major cryptocurrencies in 2022, which led to a perception of them being a poor investment. We therefore found it relevant to explore Parma and Wassvik previous findings.

The work on this thesis has been both instructive and demanding as we have explored a relatively new phenomenon within finance. We were dependent on gathering and organizing a significant amount of data, which proved to be more challenging than expected. It has required a great deal of effort, but we have truly been challenged and learned a tremendous amount. Through this assignment, we have been able to apply theories and methods that we have learned during our studies, particularly in the field of statistics, using programs such as Stata and Excel.

We want to say a big thank you to Ivar Bredesen, our tutor, for helping us with this project. The fact that he had been reviewing papers on a similar topic a few years back gave us some great ideas and added expertise and knowledge that we otherwise would not have been able to add.

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1 Introduction

1.1 Motivation:

Considering what has happened in the last year, year and a half, we wanted to explore the topic of cryptocurrency. To begin with neither of us had any deep knowledge of the topic other than the typical general idea you get from reading different news articles. Depending on what time period, news could report dramatic increases and dramatic decreases in prices related to crypto. We wanted to explore crypto further as none of us had any faith in cryptocurrency other than it was just an asset for risky speculators. We stumbled upon a previously written master thesis about cryptocurrencies. More specifically, should well-diversified portfolios contain cryptocurrency? This question intrigued us as this thesis was written back in 2018. Backed with data from 2010 until the end of 2017, their conclusion was that cryptocurrencies outperformed all assets and was a superior choice for investors. They backed their findings with different financial performance metrics.

However, the time period examined is considered a great period for cryptocurrencies and tech companies and as we looked further in their dataset something looked off. Cryptocurrencies have had a relatively stable price, however, mid 2017 until end of December 2017 something changed. In just a few weeks, Bitcoin has seen a 1573% growth, Ethereum 6523% growth and Litecoin with a growth of 2107%. These are extreme observation and taking into consideration that these positive fluctuation in prices was observed during the last 42 observations in their dataset out of 391 where prior observations have been very stable, we suspected that these extreme positive observations that deviate from the mean (outliers) can have affected their calculations, giving misleading financial metrics.

As Parma and Wassvik only saw the positive side of crypto currencies, we wanted to do a review of their findings, that a well-diversified portfolio should include cryptocurrencies, but as an investor investing in the period 2017 to 2022. This period is characterized by increased volatility, with price changes occurring in both positive and negative directions, rather than solely experiencing extreme positive price growth as seen in Parma and Wassviks dataset.

1.2 Research Question:

From the given motivation and disturbances caused by the extreme observations in Parma and Wassvik dataset, we want to revisit their study with newer data.

Our research question is therefor:

Does Parma and Wassvik's conclusion of "Should a well-diversified portfolio contain cryptocurrencies?" from the period 2010-2017 hold true when compared to the period 2017-2022 using similar data?

2 Cryptocurrency – Origin, structure and flaws

It is incredible to think that fifteen years ago, nobody had ever heard of Bitcoin or other cryptocurrencies. Today, Bitcoin and thousands of other crypto's have been made and they have had different degrees of success in the real world. The article" The *rise of bitcoin and the cryptocurrency market"* describes how Bitcoin became the first cryptocurrency, developed in 2009, and is today regarded as the most well-known cryptocurrency.

All cryptocurrencies are built on what is known as a blockchain. The blockchain can be seen as a database or ledger where all the data is shared between several computer network nodes. (Hayes, 2023). These blockchains are not limited to crypto, but it is crucial for crypto's to be legitimate. The reason is that blockchains work similarly to a spreadsheet, where data is stored in a cell. The difference is that in a blockchain all data within the cell must be changed at the same time for all the nodes. This makes a blockchain secure, because nobody can access the blockchain from one node, or computer, to change any of the cells. The blockchain would refuse the change because it would not be consistent with all the other nodes in the network. (Hayes, 2023)

See attachment 1 for how the transaction process from start to finish works.

The whole idea of Bitcoin and cryptocurrencies using the blockchain is to be transparent with records of a ledger or payment and any transaction done without the possibility to change or alter the data. This then leads to the fact that cryptocurrencies go around the typical financial institutions, like banks and so on. The idea is great and phenomenal, but the execution is difficult and still needs work. The same article" The *rise of bitcoin and the cryptocurrency market"* states that cryptocurrencies are still new and relatively untested. There are also several issues and challenges that need to be worked out for it to reach its full potential. The article points out that the lack of regulations is one of the major issues, since cryptocurrencies operate outside of the typical financial institutions.

Another issue is that Bitcoin, and cryptocurrencies in general, are often based on trust. The blockchain alone is one of the biggest reasons for trusting the coin. Trust is defined as "assured reliance on the character, ability, or truth of someone or something" (Miriam-Webster dictionary)

The article *"Fear, uncertainty and doubt: Global regulatory challenges of crypto insolvencies"* written by Natarajan et al, highlights some of the difficulties that cryptocurrencies face. They state that the crypto market is valued at less than 1 trillion dollars, due to recent events and the general decline in crypto market capitalization. Just a year earlier, in November 2021, the market was valued at almost 3 trillion dollars. Why has the market declined? There is no definitive answer, but again the article written by Natarajan et al shines a spotlight on some key aspects that could explain the decline. Firstly, categorizing and classifying what crypto assets are legally is a real challenge. There is no worldwide consensus on how the jurisdiction and agreements made between parties on how this should work. (Natarajan et al, 2023).

Secondly, asset-tracing is almost impossible, and recovery is a major problem. The fact that crypto assets are supposed to be anonymous makes tracing and recovery pretty much impossible. Anonymity is by far the biggest selling point of cryptocurrencies, but it comes at the cost of not only making it hard to trace but to recover if something goes wrong. It also has the added effect of attracting people wanting to abuse that exact reason.

Lastly, the fact that cryptocurrencies are so volatile, makes it so creditors have a hard time wanting to engage. “Between April 2022 and January 2023, Bitcoin’s value more than halved, from just over $45,000 to below $20,000. But three years ago, Bitcoin was half the current price and traded at levels below $10,000.” (Natarajan et al, 2023). This alone is a huge hurdle for creditors, because you essentially take on more risk when dealing with a cryptocurrency rather than a currency like dollars or euros.

There are different ways of ranking cryptocurrency. You could rank the currencies based on price alone, but this would not give you an accurate picture of what is the number one cryptocurrency. Crypto.com ranks the currencies based on market cap, which is the price of the coin times the circulating supply of that specific coin. Bitcoin being at the number one spot should not surprise anyone, considering this is the most well-known cryptocurrency in the world and at the same time the first one ever created.

3 Methodology

To clarify how we have structured our methodology we first have to mention some differences between Parma and Wassvik's thesis and ours. Their data is from the start of 2010 to the end of 2017, and our data is from the start of 2017 to the end of 2022. The reason we have chosen to only look at this period is mainly because it is a natural break in the data, where you can clearly see from attachment (x) that the price of Bitcoin drastically increased from mid 2017. We wanted to make sure the previous period did not create a bias or skewing of data. Considering the amount of data, we have gone for a quantitative approach to the thesis, like Parma and Wassvik. This allows us to perform the different tests and measures.

In this study, both Stata and Excel were utilized to conduct various statistical analysis and calculations. Stata, a statistical software, was primarily used for calculating descriptive statistics such as mean, skewness, kurtosis, variance, standard deviation, standard error, correlation matrix computation, hypothesis testing, and assessment of normality in our dataset. Descriptive statistics calculated in Stata were then imported to excel for further inspection.

Furthermore, hypothesis tests such as the Dickey-Fuller test for unit root, skewness and kurtosis hypothesis tests, and the Shapiro-Wilk test for normality were conducted using Stata. These tests enabled the evaluation of underlying assumptions and characteristics of the data. The arithmetic and geometric means were also computed in Stata to determine the average returns.

On the other hand, Excel was utilized for generating the variance-covariance matrix, an essential component in our portfolio analysis. The Solver function available in Excel was employed to optimize the Sharpe ratio for a given return and construct the efficient frontier. Additionally, we used the solver function to find the optimal weighted portfolio (highest Sharpe ratio) in our data set. Additionally, Excel was used for performing calculations related to the Capital Asset Pricing Model (CAPM), Sortino Ratio, Information Ratio, Sharpe Ratio, Treynor Ratio, and Jensen's Alpha. The visual presentation of findings, including tables, was facilitated through Excel's graphical capabilities.

To summarize, Stata was primarily utilized for descriptive statistics, hypothesis testing, and calculating certain measures, while Excel played a pivotal role in generating the variance-covariance matrix, solving optimization problems, and performing various calculations and visualizations.

3.1 Correlation matrix

We wanted to start off by checking the correlation between the different cryptocurrencies. The first reason was to make it more clear in the analysis of our data to only use one cryptocurrency, Bitcoin, instead of having a bunch of different cryptocurrencies like Ethereum and Dogecoin within the same data. The second reason is because Bitcoin has been "the" cryptocurrency everyone has heard of and has proven to pretty much outlast all the others. By looking at Bitcoin we would have more reliable data considering the time compared to many of the top ten most traded cryptocurrencies.

A correlation matrix is a table showing what, or by how much, a set of variables correlates. (Glen)

The correlation matrix we made shows us the different variables that have high correlations, specifically cryptocurrencies.

3.2 Diversifiable and undiversifiable risk

There is no way we can't mention and discuss the difference between diversifiable and undiversifiable risk when it comes to the topic of this thesis. We are mainly looking at financial instruments to determine whether a well-diversified portfolio should contain cryptocurrencies or not in today's markets. What does diversifiable mean, and why is this important to the topic? When someone relates to a portfolio that is well diversified, they mean a portfolio that is not exposed to firm-specific risk. Berk and DeMarzo state "Fluctuations of a stock's return that are due to firm-specific news are independent risks. Like theft across homes, these risks are unrelated across stocks, and referred to as diversifiable risk (firm-specific risk)." (Berk and DeMarzo, 2020 p. 374). So how do you minimize the amount of diversifiable risk (firm-specific risk) you are exposed to? By combining stocks that are different and preferably uncorrelated to each other and combine them into a portfolio. The bigger and more diverse the portfolio is, the less diversifiable risk you are exposed to. This makes sense, because if you have thousands of stocks in a portfolio, some of them will suddenly perform worse and others will perform better. This averages out and therefore makes you less susceptible to variations and volatility. If you instead had ten stocks in your portfolio, and one or two suddenly dropped in value due to some firm-specific news, you would be hit harder in the overall portfolio performance because of this risk. This is why a well-diversified portfolio is important to the thesis. We must make sure that we are not taking risks that are not undiversifiable, as this could change the outcome of some of the tests to see how the portfolio is performing.

3.3 Variance-Covariance matrix

Consider a dataset with two features, aiming to analyze the relationships within the data. Covariance serves as a fundamental tool for quantifying the variance between the two variables.

The covariance can be computed by adjusting the equation to calculate the variance between the two variables.

$$C_{x,y} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$$

n= Sample size
x = Observation variable x
$\bar{x}$ = Mean variable x

y= Observation variable y
$\bar{y}$ = Mean variable y

By centering the data around the mean, the equation can be simplified as:

$$C_{x,y} = \frac{x^T y}{n-1}$$

x^T= transpose of vector x

Simplifying further, the covariance calculation involves taking the dot product of two vectors containing the data.

When extending this concept to a dataset with three features (x, y, and z), the resulting covariance matrix will have dimensions of 3 by 3. This matrix captures the covariances among all features, including their variances.

$$C\,(x, y, z) = \begin{matrix} var_x & covar_{x,y} & covar_{x,z} \\ covar_{y,x} & var_y & covar_{y,z} \\ covar_{z,x} & covar_{z,y} & var_z \end{matrix}$$

The covariance matrix exhibits symmetry, with diagonal elements representing the variances of individual features, and off-diagonal entries representing the covariances between different feature pairs. To compute the covariance matrix, the vectors in the equation can be replaced with the mean-centered data matrix.

$$C_{x,y} = \frac{X^T X}{n-1}$$

X^T =transpose of the data matrix X
X= data matrix of X

n= observations

Once the covariance matrix is obtained, it can be interpreted in a similar manner as the correlation coefficient. (Lanhenke, 2021)

3.4 Skewness and Kurtosis

We remember very well how important both Skewness and Kurtosis are to a dataset. In our course Risk management this was emphasized. Skewness happens when you have a distribution of return that is not normal, and where either negative or positive outcomes are more likely than the counterpart. (Bodie, et al. p 139) Skewness is a statistical measure that describes the degree of asymmetry in a distribution of data. A symmetrical distribution has a skewness value of 0, while a distribution that is skewed to the left (i.e., has a longer left tail) has a negative skewness value, and a distribution that is skewed to the right (i.e., has a longer right tail) has a positive skewness value. (National Institute of Standards and Technology)

Skew = Average $\left[\frac{(R - \underline{R})^3}{\hat{\sigma}^3}\right]$

Equation taken from Bodie et al p. 138.

Negative values will still be negative because Skew takes that into consideration when powering with an odd number. Equally, positive numbers will stay positive.

“Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. That is, data sets with high kurtosis tend to have heavy tails, or outliers. Data sets with low kurtosis tend to have light tails, or lack of outliers. A uniform distribution would be the extreme case. The histogram is an effective graphical technique for showing both the skewness and kurtosis of data set.” (National Institute of Standards and Technology)

The kurtosis measures the degree of “peakedness”, or “flatness” of a distribution compared to a normal distribution. A kurtosis value of 3 indicates a normal distribution (mesokurtic), values greater than 3 indicate a more peaked distribution (i.e. leptokurtic), and values less than 3 indicate a flatter distribution (i.e. platykurtic). (Kenton, 2023)

Kurtosis = Average $\left[\frac{(R-\underline{R})^4}{\hat{\sigma}^4}\right]-3$

Equation taken from Bodie et al p. 139

3.5 Arithmetic and geometric averages

An expected return on an investment is important for investors. Risk on the other hand could be equally important as the expected rate of return. Sadly, the real world is not how the theory on risk and return is written ends up being. Most theories are based on the market and the investors being rational. We all know that this is often far from the truth, and therefore it is very difficult to identify the actual return and risk. (Bodie et al, 2021 p. 119) Risks and returns are pretty much impossible to accurately observe. But there is a fix to the problem, realized returns. Bodie et al, states this about realized returns “These provide noise estimates of the expected returns and risk that investors actually anticipated.”, but no matter how much you look back to try and predict the future you will never be truly able to expect what ends up happening.

Parma and Wassvik used both the arithmetic average and the geometric mean in their thesis. The arithmetic average takes all the returns and divides them by the number of returns (observations). As we have stated above, we use past returns to try and calculate an estimate of the future return. Usually, the return one period ahead is highly correlated to the return that just happened, but there are unexpected things that can happen, which could alter the actual return and therefore make the estimate very wrong.

The geometric mean is often used in economics because it is commonly used for growth rates and so on. It is important to remember that you can only get a geometric mean for positive numbers.

$$GM = \sqrt[n]{(x_1 * x_2 * x_3 \ldots x_n)}$$

Equation is taken from Glen (Geometric Mean…)

Here you take all the returns and multiply them, then you take the number of observations and power that to the square root.

3.6 Augmented Dickey-Fuller test

The Augmented Dickey Fuller test is a test to see whether your data has a unit root. In other words, you can use the test to check if your data fluctuates around a mean or not. A stationary dataset would typically have the mean, variance and covariance be constant around some point in the dataset. (Glen). This point could be the average, or it could be another point of which the data revolves around. The null-hypothesis of the ADF (Augmented Dickey-Fuller test) is that there is a unit root. And the alternative is that there is not a unit root. If the p-value is lower than the critical value set, we reject the null hypothesis that there is a unit root. (Stock and Watson. 2020, p 586-589) It is important to mention that the augmented Dickey-Fuller test adds as many lags to the regression as is needed to make sure that the residuals of those regressions do not interfere. (MacKinnon, 2010)

3.7 Shapiro–Wilk test for normality

The Shapiro-Wilk test is a test to see how far from normality our sample is. Skewness, kurtosis or a combination of both is usually the reason we have deviations from a normal sample distribution. The Shapiro-Wilk test is given by:

$$W = \frac{\left(\sum_{i=1}^{n} a_i y_i\right)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

y_i is the i’th order statistic.

$\bar{y}$ is the sample mean.

The W value will be between 1 and 0. The lower the number, closer to 0, the more our sample deviated from a normal distribution, given our sample. And if you get a W value of 1, your sample does not deviate from a normal distribution at all. (Razali and Wah. 2011)

3.8 Capital Asset Pricing Model

The capital asset pricing model, often shortened to CAPM, allows us to figure out what the efficient portfolio is without knowing the expected return of each security. This is probably one of the most well-known financial instruments, used to predict the relationship between the expected return and a risky asset (Bodie, et al. 2021). It was 1952, when Harry Markowitz formed the foundations of what would later become the capital asset pricing model. Articles, written by William Sharpe, John Lintner and Jan Mossin in 1964, about the CAPM would be the beginning of one of the most fundamental centerpieces of modern financial economics. (Bodie, et al. 2021 p. 275-277) The CAPM takes into consideration what choices investors make to create and identify the efficient portfolio as the market portfolio (Berk and DeMarzo, 2020 p. 421-425). To do this the CAPM has three assumptions.

1. *Investors can buy and sell all securities at competitive market prices (without incurring taxes or transaction costs) and can borrow and lend at the risk-free interest rate.*
2. *Investors hold only efficient portfolios of traded securities-portfolios that yield the maximum expected return for a given level of volatility.*
3. *Investors have homogeneous expectations regarding the volatilities, correlations, and expected returns of securities.*

(The assumptions are taken directly from Berk and DeMarzo 2020, page 421-422)

$ERi = Rf + \beta i(ERm - Rf)$

Where:

ERi = expected return of investment

Rf = risk-free rate

βi = beta of the investment

($Erm - Rf$) = market risk premium

The equation and explanation of variables are all taken directly from Kenton, 2023. Investopedia.

3.9 Jensen's Alpha

Jensen's Alpha is a risk-adjusted performance measure in finance. It takes into consideration the CAPM and shows whether your average return on a portfolio is below or above the predicted CAPM, given the average market return or the beta. The beta could either be the investments or the portfolio's beta. (Chen, 2023) By subtracting the required return for an asset given by the CAPM from the actual return we get Jensen's Alpha. A positive Jensen's Alpha indicates that the asset performed better than expected and a negative value shows the asset underperformed.

$$\alpha = R_i - (R_f + \beta\left(R_m - R_f\right))$$

Where:

R_i = the realized return of the portfolio investment

R_m = the realized return of the appropriate market index

R_f = the risk-free rate of return for the time period

β = the beta of the portfolio of investment with respect to the chosen marked index

The equation and explanation of variables were all taken directly from Chen, 2023. Investopedia.

3.10Treynor Ratio

The Treynor ratio, commonly known as the reward to volatility ratio, is a metric that shows how much excess return is generated for each unit of risk taken on by the portfolio. (Kenton, 2020). In other words, excess return means how much more you earned versus in a risk-free investment. In finance we often calculate with risk-free investment/return/rate. Although there is no such thing as a risk-free investment, we usually say that treasury bills are close to what a risk-free investment would be. This is what we will also use in this thesis, the three-month treasury bill as the risk-free rate.

Treynor ratio = $\frac{r_p - r_f}{\beta_p}$

Where:

r_p = Portfolio return

r_f= Risk-free rate

β_p = Beta of the portfolio

The equation and explanation of variables are all taken directly from Kenton, 2020. Investopedia.

3.11 Information Ratio

The Information ratio is similar to the Sharpe ratio, but instead of dividing it by the standard deviation (of the portfolio's excess return) you divide it by something called the “tracking error”. The tracking error is referred to as “the standard deviation of a security or portfolio returns from the returns of a benchmark” (Team, CFI, 2023 Information ratio). This is the biggest difference between the Sharpe ratio and Information ratio. The Sharp ratio is a risk-adjusted measure that compares to the risk-free rate and the Information ratio compares to a benchmark. Although there is no “true” risk free rate in the real world, it is usually true that a medium-long Treasury Bill is as close to a risk-free rate as we need to do the calculations. One of the main users of the Information ratio are fund managers. This is because the information ratio provides insight into whether the fund manager can maintain or keep the generation of excess or abnormally high returns over time. (Team, CFI, 2023. Information ratio)

“The information ratio is a measurement of portfolio returns beyond the returns of a benchmark, usually an index, compared to the volatility of those returns” (Murphy, 2020)

Information ratio = $\frac{E(R_i - R_b)}{\sigma_{ib}}$

Where:

R_i = the return of a security or portfolio

R_b = the return of a benchmark

$E(R_i – R_b)$ = the expected excess return of a security or portfolio over benchmark

σ_{ib} = the standard deviation of a security or portfolio returns from the returns of a benchmark (tracking error)

The equation and explanation of variables are all taken directly from Team, CFI, 2023. Information ratio. Corporatefinanceinstitue.

3.12 Sharpe Ratio

The Sharpe ratio is a very common way of measuring risk-adjusted relative returns. It divides the excess return of the portfolio by a measure of volatility to see what the risk-adjusted performance is. (Fernando, 2022) It is very common for investors to want the most amount of money back, highest possible return, but at same time have the smallest chance of losing the money they invested, lowest possible risk. The Sharpe ratio basically allows investors to figure if the extra risk they are taking on by investing is going to be worth it by getting higher compensation, higher return. (Baldridge and Curry. 2022)

During this thesis our aim is to find out if a well-diversified portfolio should contain cryptocurrency or not, and the Sharp ratio is just an excellent financial instrument to help us answer that question. The fact that the Sharpe ratio allows us to see how much risk someone would have to take on in a portfolio containing cryptocurrencies, to get their desired return is just perfect. This is one of the reasons why Parma and Wassvik chose to include this instrument to answer their thesis and the rason we wanted to include it as well.

The way the Sharpe ratio works is the higher the ratio the better the investment is, based on risk-adjusted returns. (Baldrige and Curry. 2022) According to Baldrige and Curry, a Sharpe ratio between 1 and 2 is considered good. A ratio between 2 and 3 is very good, and anything above 3 is excellent. The only downside to the Sharpe ratio is the fact that the denominator is the standard deviation. This implies that the ratio expects a normal distribution. Often this is not the case in the real world. This could make the result of the calculation wrong, so it is important to not use the results of the ratio as a definitive answer. But it is a great indication of return considering the risk taken on. (Baldrige and Curry. 2022)

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Where:

Rp = return of portfolio

Rf = risk-free rate

σp = standard deviation of the portfolio’s excess return

The equation and explanation of variables were all taken directly from Fernando, 2022. Investopedia.

3.13 Omega Ratio

Just like the Information ratio, the Omega ratio builds on the principles of the Sharpe ratio. As stated in the Sharpe ratio paragraph the ratio is built on the fact that the distribution is normal. The Omega ratio on the other hand, is not built on the distribution being normal. (DeLee, 2023)

$$\Omega = \frac{Percent\ Change\ in\ V}{Percent\ Change\ in\ S}$$

Where:

V = Price of the option

S = Underlying price

The equation and explanation of variables were all taken directly from Scott, 2022. Investopedia.

3.14 Sortino Ratio

Just like the Information- and Omega ratios, the Sortino ratio is a variation of the Sharpe ratio. This time the way Sortino differs from Sharpe is when looking at only the downside risks of an investment. While the Sharpe ratio looks at both upsides and downsides of the risk taken on, the Soritno ratio provides an accurate return given the likelihood of a set downside risk. (Team, CFI, 2023. Sortino ratio)

The Sortino ratio is a modified version of the Sharpe ratio that distinguishes detrimental volatility from total overall volatility. This is achieved by incorporating only the standard deviation of negative portfolio returns, also known as downside deviation, instead of the total standard deviation of portfolio returns. To calculate the Sortino ratio, the excess return of an asset or portfolio is divided by its downside deviation after subtracting the risk-free rate. (Kenton, 2020. Sortino Ratio)

$$S = \frac{(R-T)}{DR}$$

Where:

S = Sortino ratio

R = Average realized return

T = Required rate of return

DR = Targeted downside deviation

The equation and explanation of variables are all taken directly from Team, CFI, 2023 Sortino ratio. Corporatefinanceinstitue.

3.15 Efficient frontier

The efficient frontier is a concept in modern portfolio theory (MPT) that represents a set of optimal portfolios offering the highest expected return for a given level of risk or the lowest risk for a specific expected return. Portfolios lying below the efficient frontier are considered suboptimal because they do not provide enough return for the risk taken, while portfolios clustering to the right of the efficient frontier have a higher level of risk for a given rate of return.

The efficient frontier is graphically represented with return on the y-axis and risk (typically measured by standard deviation) on the x-axis. It depicts the tradeoff between risk and return in portfolios. The goal is to construct portfolios that maximize returns while minimizing risk by combining securities with lower covariance (less synchronized) to reduce the overall standard deviation.

Diversification plays a crucial role along the efficient frontier. Optimal portfolios that lie on the efficient frontier tend to be more diversified, offering a higher degree of risk reduction compared to sub-optimal portfolios. Diversification improves the risk/reward profile of the portfolio and demonstrates the diminishing marginal return to risk.

However, the efficient frontier and MPT have certain assumptions that may not reflect reality. For example, they assume that asset returns follow a normal distribution, which may not always be the case. Critics argue that real-world markets involve irrational investors, market influences from large participants, and limited access to borrowing and lending money.

To use the efficient frontier, a risk-seeking investor would select investments on the right side of the frontier, which have higher risk and potential returns. On the other hand, a more conservative investor would choose investments on the left side, which offer lower risk and expected returns.

In summary, the efficient frontier helps investors understand the optimal balance between risk and return in portfolio construction. It highlights the benefits of diversification and guides investors in selecting portfolios that offer the highest expected return for a given level of risk or the lowest risk for a specific expected return. (Berk and DeMarzo. 2020, p 412-420) (Ganti, 2022)

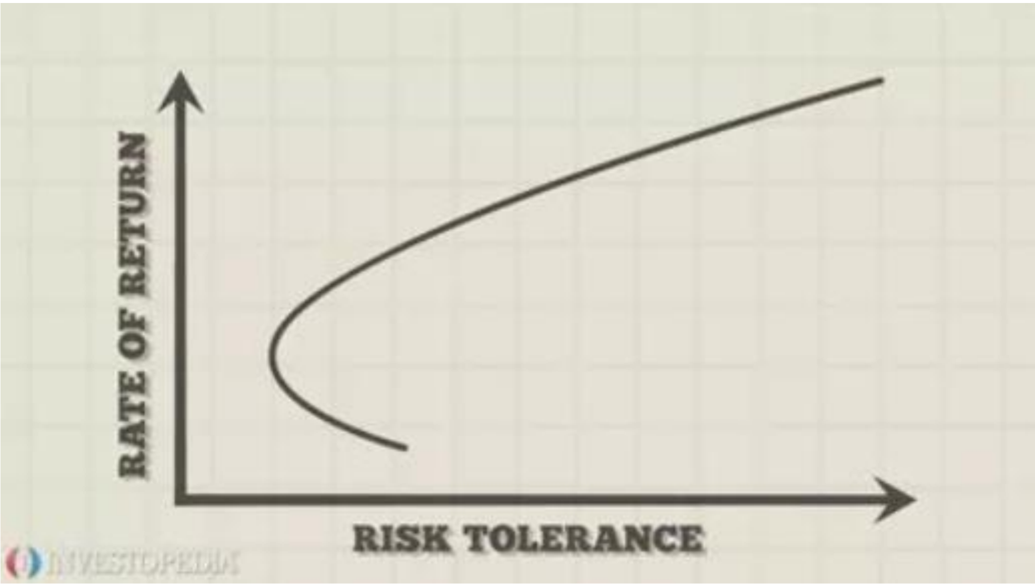


Figure 1: Efficient frontier

(Source for figure: https://www.investopedia.com/terms/e/efficientfrontier.asp)

4 Data

In this chapter, we will discuss the datasets used in our thesis. We'll explain how we collected and transformed the data. We will also talk about the limitations and weaknesses of these datasets.

4.1 Data used in Parma and Wassvik:

As our research question emphasizes, “Does Parma and Wassvik’s conclusion of “Should a well-diversified portfolio contain cryptocurrencies?” from the period 2010-2017 hold true when compared to the period 2017-2022 using similar data?”**,** our thesis was dependent on getting the same data set as Parma and Wassvik for a valid comparison of Crypto currencies performance compared to the assets they used.

Assets used in Parma and Wassvik is the following:

- Thomson Reuters Global Emerging Markets Index
- HFRX Global Hedge Fund CAD Index
- MSCI International World Real Estate Price Index USD Realtime
- MSCI International World Price Index USD Realtime
- Thomson Reuters Global Developed Index
- ICE Brent Crude Electronic Energy Future Continuation 1
- S&P Global Developed Sovereign Bond Index
- FTSE EPRA/NAREIT Global Index
- Thomson Reuters SGX Corporate Bonds 3+ Years Index
- PowerShares Emerging Markets Sovereign Debt ETF
- SPDR Citi Int. Govt. Inflation-Protected Bond ETF
- US Dollar / Japanese Yen FX Spot Rate
- Euro / US Dollar FX Spot Rate
- UK Pound / US Dollar FX Spot Rate
- Gold / US Dollar FX Spot Rate

The funds and indices used by Parma and Wassvik were similar to the once used in the articles “Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin” by Briére, M., Oosterlinck, K., and Szafarz, A. (2015).

All their assets were 419 weekly observations of closing prices except for Bitcoin which had 391 weekly observations, Litecoin which had 220 weekly observations and Ethereum with only 126 observations. This means Parma and Wassvik had weekly data from 01.01.2010 for all non-crypto currencies’ assets, weekly data from 09.07.2010 for Bitcoin, weekly data from 18.10.2013 for Litecoin and weekly data from 31.07.2015 for Bitcoin. The last observation for all their assets was 29.12.2017.

4.2 Data used in our thesis.

As this thesis goal is to do a reevaluation of Parma and Wassvik's findings, it was critical to get the same dataset as them only with updated observations ending in 31.12.2022. The following data from their paper was used in our research:

- Thomson Reuters Global Emerging Markets Index
- HFRX Global Hedge Fund CAD Index
- MSCI International World Real Estate Price Index USD Realtime
- MSCI International World Price Index USD Realtime
- Thomson Reuters Global Developed Index
- ICE Brent Crude Electronic Energy Future Continuation 1
- S&P Global Developed Sovereign Bond Index
- FTSE EPRA/NAREIT Global Index
- Thomson Reuters SGX Corporate Bonds 3+ Years Index
- PowerShares Emerging Markets Sovereign Debt ETF
- SPDR Citi Int. Govt. Inflation-Protected Bond ETF
- US Dollar / Japanese Yen FX Spot Rate
- Euro / US Dollar FX Spot Rate
- UK Pound / US Dollar FX Spot Rate
- Gold / US Dollar FX Spot Rate
- Bitcoin/Usd
- Ethereum/Usd
- Litecoin/Usd

As we did not have access to all assets in the correct time period, we downloaded the following assets as a substitution:

- Invesco Emerging Markets Sovereign Debt ETF
- MSCI International ACWI Price Index USD
- US 10 Years Treasury Note

We also used the following additional data to construct our own benchmark against cryptocurrencies:

- S&P 500
- S&P GSCI (commodities)
- S&P BSE SENSEX (India)
- S&P/ASX 200 (Australia)
- MOEX Russia Index
- S&P Latin America 40
- S&P Africa 40 Index
- Europe Stoxx 600
- SSE Composite Index (000001.SS)(Shanghai)

4.3 Data collection and datasets

We used four sources for our data, Parma and Wassvik data set, Eikon Reuters, S&P and Yahoo Finance.

Following data was extracted from Parma and Wassvik:

- ICE Brent Crude Electronic Energy Future Continuation 1
- HFRX Global Hedge Fund CAD Index
- Thomson Reuters SGX Corporate Bonds 3+ Years Index
- PowerShares Emerging Markets Sovereign Debt ETF

These are 419 weekly observations all ranging from 01.01.2010 - 29.12.2017. We could not find these in assets in either Eikon Reuters or Yahoo Finance.

Following data was extracted from Eikon Reuters:

- Invesco Emerging Markets Sovereign Debt ETF
- MSCI International ACWI Price Index USD
- Thomson Reuters Global Emerging Markets Index
- MSCI International World Real Estate Price Index USD Realtime
- MSCI International World Price Index USD Realtime
- Thomson Reuters Global Developed Index
- S&P Global Developed Sovereign Bond Index
- FTSE EPRA/NAREIT Global Index
- SPDR Citi Int. Govt. Inflation-Protected Bond ETF

We extracted 642 weekly observations ranging from 17.09.2010 to 29.12.2022. We then reduced the amount to 316 observations, capturing the weekly closing prices ranging from 30.12.2016 to 06.01.2023.

Following data was extracted from Yahoo Finance:

- US Dollar / Japanese Yen FX Spot Rate
- Euro / US Dollar FX Spot Rate
- Pound / US Dollar FX Spot Rate
- Gold / US Dollar FX Spot Rate
- Bitcoin/USd
- Litecoin/usd
- Ethereum/Usd
- Europe Stoxx 600
- SSE Composite Index (000001.SS)(Shanghai)
- MOEX Russia Index

We extracted as many weekly observations as possible and then reduced the observations to 316, capturing the weekly closing prices between 30.12.2016 to 06.01.2023

Following data was extracted from S&P500:

- S&P 500
- S&P GSCI (commodities)
- S&P BSE SENSEX (India)
- S&P/ASX 200 (Australia)
- S&P Latin America 40
- S&P Africa 40 Index

Again, as with the previous data, we extracted weekly closing prices as far back as possible, then reduced to 316 observations, capturing the weekly closing prices between 30.12.2016 to 06.01.2023.

We created in total three different datasets for our calculations.

Our first dataset consists of 314 logged observations of weekly closing prices capturing the period from 2017-2022. This is our main set that almost all our calculations are based on. To start our observations on 30.12.2016 was natural as Parma-Wassvik ended their observations in this period. We also "captured" the big positive and negative price movements observed from 09.07.2010 to December 2022 making sure we got observations both over and under the mean and not only extreme upward price movement as in Parma and Wassvik. We will also argue that cryptocurrencies first got its place in mainstream media during 2017, attracting the "average" investor, hence this time being a good time to analyze if cryptocurrencies should be included in a well-diversified portfolio for an investor investing in 2017-2022.

Mostly, all the assets used in Parma-Wassvik except for some as we did not get access to or updated prices on the following assets:

- HFRX Global Hedge Fund CAD Index
- Thomson Reuters SGX Corporate Bonds 3+ Years Index
- PowerShares Emerging Markets Sovereign Debt ETF
- Brent Crude Electronic Energy Future Continuation 1

Instead, we included:

- MSCI International ACWI Price Index USD Real time
- Invesco Emerging Markets Sovereign Debt ETF
- US 10 Years Treasury Note

We also created and included an index we thought would be a better benchmark than MSCI International world price index to measure cryptocurrencies that reflected the average cryptocurrencies trader's investment opportunity. This portfolio is called "own portfolio" and consists of 9 indexes weighted after the percentage of which country trades most cryptocurrencies. This market portfolio serves as a benchmark for cryptocurrencies, and its composition is determined by the distribution of crypto traders across countries. For instance, if 50% of all crypto traders reside in the US, the portfolio will allocate 50% to the S&P 500 index, as it represents an alternative investment choice for US traders. Similarly, percentages of trades in China and India will determine the corresponding weights of their respective indexes. In this way, the "Own Portfolio" offers a benchmark that mirrors the preferences of the average crypto investor.

As our second dataset, we used Parma and Wassvik's data with some modifications. For this dataset, we were interested in seeing how Bitcoin alone would contribute to a portfolio with normal assets. To exclude missing bitcoin observations, we started the observations on 16.07.2010 as this was the first Bitcoin observation and ended on 29.12.2017. This gave us 390 logged observations that we used to create the efficient frontier and how bitcoin would be weighted in the optimal weighted portfolio using excel solver.

Our third data set also uses Parma and Wassvik's data, here we include all their assets to see how Bitcoin, Litecoin and Ethereum would affect a portfolio and how they would be weighted in the optimal weighted portfolio using the efficient frontier. However, we only used the observations from 31.07.2015 to 29.12.2017. This is 126 logged observations. The reason we only did 126 observations was because we did not want any missing values as Ethereum was first introduced on 31.07.2015 and more accurate variance since the mean for Bitcoin and Litecoin is higher.

The main reason why we used weekly data was to have the same data structure as Parma and Wassvik as they used it in their calculations. Weekly closing prices are also widely used in financial analysis to smooth out daily volatility, identify trends, and provide a long-term perspective on a stock's performance (Hayes, 2021). And as explained by Parma and Wassvik, "cryptocurrencies do not have the same limitations as stock and bond markets. Trade happens even on weekends, public holidays and holidays. That means using daily data would have provided data for Saturday and Sunday, which we then had to trim out. Using weekly data also makes it possible to "trim" out observations on holidays and other days where there was no trade, as they are incorporated in a weekly observation" (Parma-Wassvik).

We used Excel to store and combine data for further calculations.

4.4 Risk Free interest rate.

Parma and Wassvik's thesis mentioned that Duff & Phelps recommended a risk-free return of 3.5%. We agree with this suggestion considering that the current 10-year treasury yield is approximately 3.5% and we can consider it as a close approximation of a risk-free rate (Bloomberg). However, it is important to note that there is no definitive risk-free rate, and determining a universally accessible risk-free rate for all investors is challenging. However, we have opted to use the rate of 3.5% reflecting the 10-year treasury yield, it is also a theoretical number used as the risk-free rate in many examples in our classes at OsloMet.

4.5 Our two benchmarks, MSCI International World Price Index and our own created market portfolio.

Parma and Wassvik use the MSCI as their benchmark. The MSCI World Price Index comprises over 1600 securities from 23 developed countries across the globe (MSCI n.d.). These characteristics render the MSCI World Price Index significantly more appropriate as a benchmark than the S&P 500 taking into consideration that Crypto is a worldwide traded asset. Ryan Barnes (2018) advocates for the use of MSCI as an international benchmark (Barnes 2018).

However, considering that cryptocurrencies are not confined to a single wealthy country but traded around the world, we believe that utilizing an international index that reflects the average crypto investor's opportunity is important. We aimed to incorporate our "own portfolio" as it effectively captures the average cryptocurrency investor's market preferences. It is important to note that the MSCI, being focused on developed countries, may not accurately represent the cryptocurrency market, as a substantial number of crypto investors are situated in non-developed countries like Nigeria and Colombia and don't have the opportunity to invest in the MSCI index.

By incorporating our "Own Portfolio" alongside the argument previously presented for using the MSCI as a benchmark, we aim to provide a more comprehensive representation of the cryptocurrency market. Unlike the MSCI, which predominantly focuses on developed countries, our approach acknowledges that many crypto investors are located outside of developed countries. This inclusivity ensures that our benchmark aligns more accurately with the global cryptocurrency landscape.

Our "Own Portfolio" serves as a benchmark for cryptocurrencies, allowing us to better gauge the average investor sentiment. We have weighted the portfolio based on the percentage of cryptocurrency traders in each country.

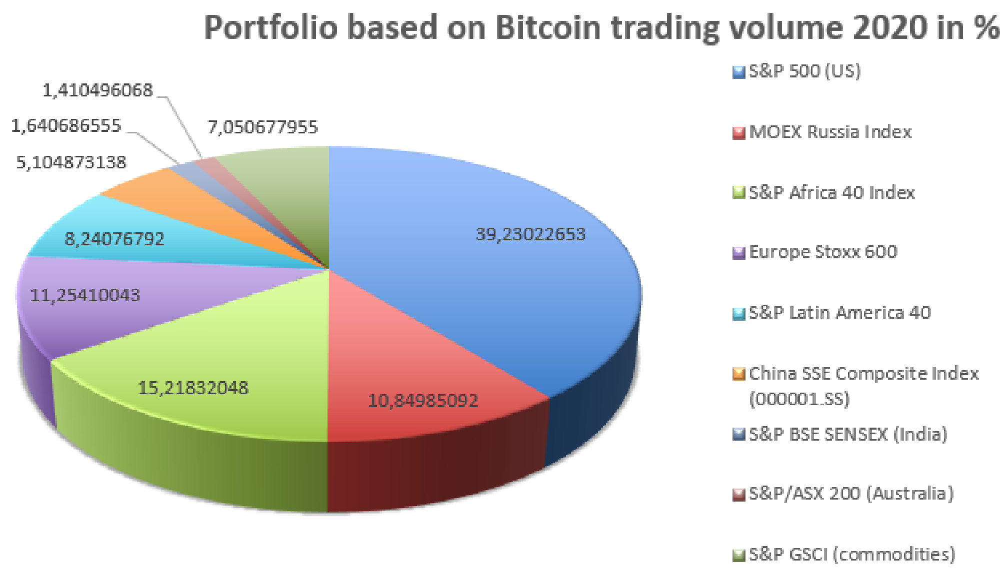


Figure 2: Portfolio based on Bitcoin trading volume

Source for figure: Statista

We have weighted our portfolio based on a survey conducted by Statista estimate (Statista estimates) on Bitcoin trading volume by countries. For example, 39.2% of all cryptocurrency traders lived in the USA during 2020, our portfolio will allocate 39.2% to the S&P 500 index, as US traders could have potentially invested in the S&P 500. Similarly, 15.2% of crypto traders lived in Africa, therefore, 15.2% of our portfolio will be allocated to the S&P Africa 40 Index to represent their investment opportunities. The rest of our own market portfolio consist of, 11.25% of Europe Stoxx 600, 10.84% of MOEX Russia index, 8.24% of S&P Latin America 40, 7.05% of S&P GSCI Commodities (Banton, 2022). 5.1 of China SSE Composite Index, 1.64% in S&P BSE SENSEX India and the rest in S&P/ASX 200 Australia.

We created this market portfolio with the assumption that the market is not efficient, meaning capital cannot be or is difficult to be invested across borders. This can somewhat be true as we have seen a growing trend with economic restrictions during the last years.

4.6 Weaknesses and Limitations:

One major weakness of our study is the lack of access to the same dataset used by Parma and Wassvik. We were able to include most of the same investment objects; however, we encountered discrepancies as Thomson Reuters SGX Corporate Bonds 3+ Years Index, PowerShares Emerging Markets Sovereign Debt ETF, ICE Brent Crude Electronic Energy Future Continuation 1, and HFRX Global Hedge Fund CAD Index were absent from our dataset. This discrepancy creates a limitation in directly comparing the results and could introduce potential biases that may impact the overall conclusions.

Another weakness is the limited selection of cryptocurrencies in our analysis. We focused solely on Bitcoin, Litecoin and Ethereum. This limitation may affect the representativeness of our findings since the cryptocurrency market is highly volatile and diverse. By excluding other cryptocurrencies, we may miss out on potential variations and trends that could influence the overall conclusions.

Furthermore, our study analyzes data from a relatively short time period, specifically from 2017 to 2022. This time span may be considered insufficient for capturing long-term trends, market cycles, and potential variations in investment performance. Consequently, the conclusions drawn from this limited timeframe may not fully encompass the overall dynamics and potential risks associated with including cryptocurrencies in a well-diversified portfolio.

Moreover, it is important to note that the ranking of cryptocurrencies by market capitalization has changed since the period analyzed by Parma and Wassvik. For instance, Litecoin, which was ranked fifth in their study (CoinMarketCap, 2017) has dropped to the 13th position as of the current date 13.05.2023(CoinMarketcap, 2023). By maintaining the same cryptocurrencies for comparison purposes, our analysis may overlook potential opportunities or risks associated with other cryptocurrencies that have gained prominence in recent years.

Another limitation is that a considerable portion of financial theory is based on the assumption of normally distributed data, which does not hold true in many real-world cases. This reliance on normal distribution can present a weakness, as it may lead to an inaccurate portrayal of the actual behavior and characteristics of financial observations, potentially resulting in misleading conclusions and financial metrics. (Chen. 2023)

Addressing these weaknesses and limitations is crucial to ensure a comprehensive and accurate understanding of our research findings and should be taken into account for further research.

5 Empirical results

Throughout our empirical analysis, we present our findings using figures and tables. The data covers the period from 2017 to 2022. Additionally, we include relevant findings from Parma and Wassvik's research conducted from 2010 to 2017, if applicable, to facilitate a clear comparison between their results and ours. The results are categorized according to the performance measures outlined in our methodology chapter.

For some performance measures, we provide results based on calculations using both the MSCI international world price index and our own constructed portfolio. However, in many cases, we only present matrices calculated using the MSCI international world price index, which is consistent with Parma and Wassvik's methodology.

In summary, cryptocurrencies demonstrate stronger performance compared to our own constructed portfolio than to the MSCI international world price index. Readers interested in all the results calculated using our constructed portfolio can refer to the data attachment for further details.

5.1 Unit root

As we are working with time series, it is important to establish that our data is stationary so our descriptive statistics like mean, variance and standard deviation used in our calculations stays the same and does not change over time. “A stationary time series Yt has a constant mean and variance, and its probability distribution does not change over time. If a series is non-stationary, conventional hypothesis tests, confidence intervals and forecasts can be unreliable” (Stock & Watson, 3rd edition Chapter 14 or 4th edition Chapter 15).

As there are no obvious breaks in our dataset, trends were the biggest concern. “A series is said to exhibit a trend if it has a persistent long-term movement” (Stock & Watson, 3rd edition Chapter 14 or 4th edition Chapter 15). As financial assets prices tend to follow a trend, we had to make the data stationery.

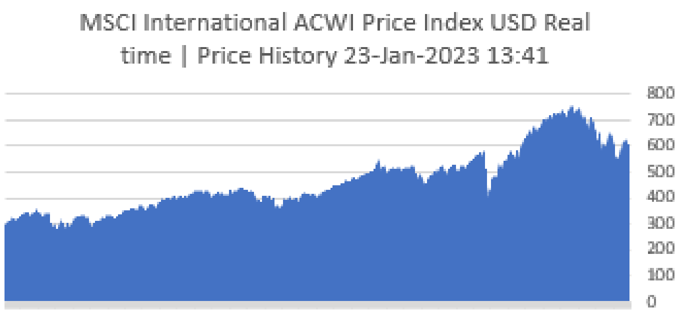
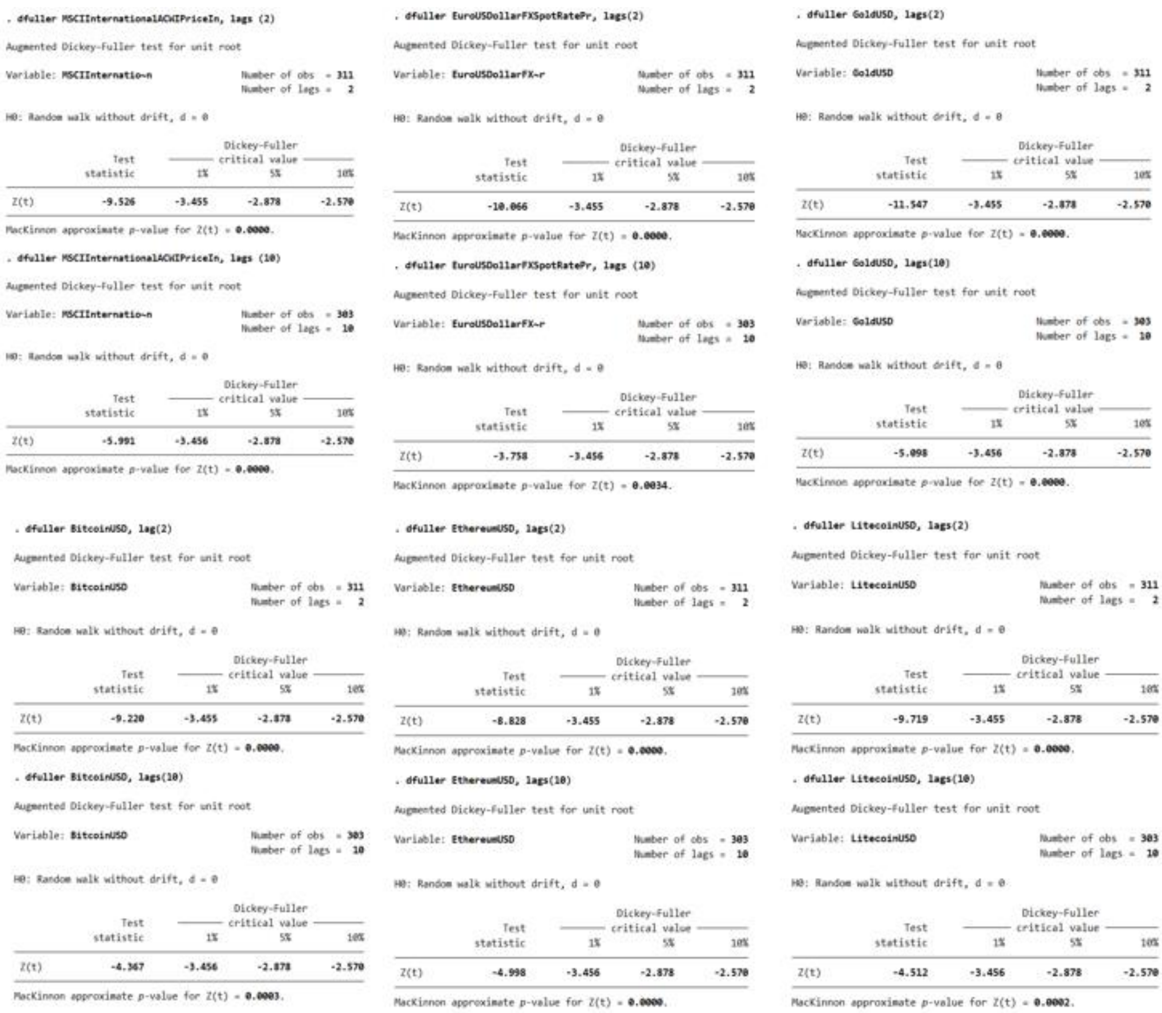


Figure 3: MSCI weekly closing price trend

MSCI International ACWI Price Index has clearly followed an upward trend from 2010-2022, meaning it will be not stationary and mean and variance will change. In order to make a time series stationery, we transformed the weekly returns into logarithmic form.

5.2 Augmented dickey fuller test

After transforming our weekly returns to logarithmic form, we performed an augmented dickey fuller test with 2 and 10 lags for all our assets to test for unit roots (Figure 4). Please refer to the attached file for the results of the Augmented Dickey-Fuller test conducted on all assets.



```
. dfuller MSCIInternationalACWIPriceIn, lags (2)

Augmented Dickey-Fuller test for unit root

Variable: MSCIInternatio~n                   Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -9.526       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller MSCIInternationalACWIPriceIn, lags (10)

Augmented Dickey-Fuller test for unit root

Variable: MSCIInternatio~n                   Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -5.991       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller EuroUSDollarFXSpotRatePr, lags(2)

Augmented Dickey-Fuller test for unit root

Variable: EuroUSDollarFX~r                   Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)           -10.066       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller EuroUSDollarFXSpotRatePr, lags (10)

Augmented Dickey-Fuller test for unit root

Variable: EuroUSDollarFX~r                   Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -3.758       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0034.
```

```
. dfuller GoldUSD, lags(2)

Augmented Dickey-Fuller test for unit root

Variable: GoldUSD                            Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)           -11.547       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller GoldUSD, lags(10)

Augmented Dickey-Fuller test for unit root

Variable: GoldUSD                            Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -5.098       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller BitcoinUSD, lag(2)

Augmented Dickey-Fuller test for unit root

Variable: BitcoinUSD                         Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -9.220       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller BitcoinUSD, lags(10)

Augmented Dickey-Fuller test for unit root

Variable: BitcoinUSD                         Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -4.367       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0003.
```

```
. dfuller EthereumUSD, lags(2)

Augmented Dickey-Fuller test for unit root

Variable: EthereumUSD                        Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -8.828       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller EthereumUSD, lags(10)

Augmented Dickey-Fuller test for unit root

Variable: EthereumUSD                        Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -4.998       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller LitecoinUSD, lags(2)

Augmented Dickey-Fuller test for unit root

Variable: LitecoinUSD                        Number of obs  = 311
                                             Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -9.719       -3.455       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

. dfuller LitecoinUSD, lags(10)

Augmented Dickey-Fuller test for unit root

Variable: LitecoinUSD                        Number of obs  = 303
                                             Number of lags =  10

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -4.512       -3.456       -2.878       -2.570
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0002.
```

Figure 4: Augmented dickey fuller tests

As the p value is below the critical value of 0.05, we reject the null hypothesis for all assets that the time series has a unit root and is nonstationary with less than 5% changes of a type 1 error.

The results from the augmented dickey fuller test can be confirmed by visualizing the data in a time series plot (figure 5).

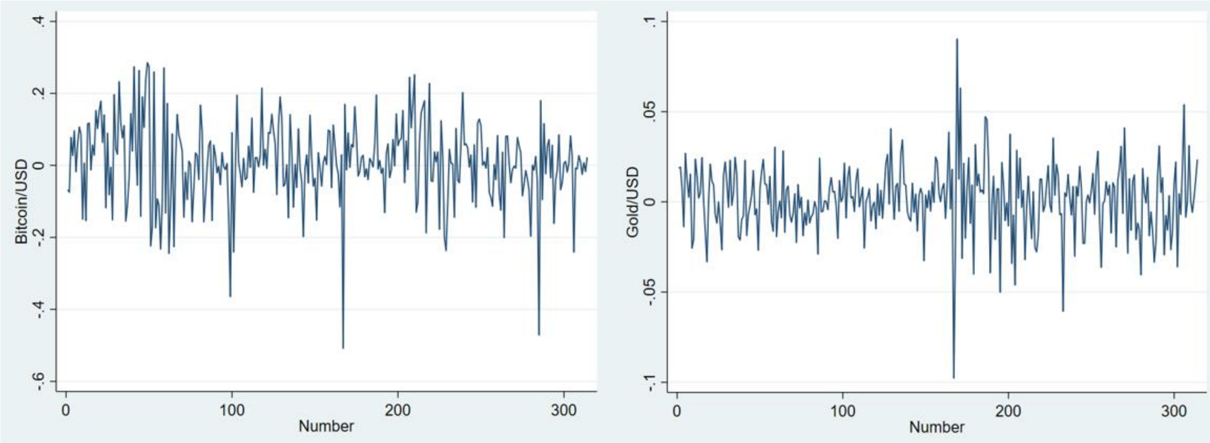


Figure 5: Time series plot

Example above shows the time series data plot for Bitcoin/USD and Gold/USD. We can see that the logarithmic return does not follow a trend but stays within a range, this indicates stationarity. All our assets are stationary in logarithmic form and readers can refer to the data attachment for further details.

5.3 Descriptive statistic

Since we have stationarity, we can use the descriptive statistic calculated in Stata knowing they will not change. We have the following metrics: number of observations (n), standard deviation (SD), mean, median (p50), maximum observation (max), minimum observation (min), range of values (range), variance, skewness, kurtosis and standard error (IQR) for weekly observations.

```
. . asdoc sum, stat(N sd mean median range min max var skewness kurtosis iqr)
(File Myfile.doc already exists, option append was assumed)
```

	N	SD	Mean	p50	Range	Min	Max	Variance	Skewness	Kurtosis	IQR
MSCIIntern~n	314	.0244403	.001213	.0026173	.2318107	-.132267	.0995437	.0005973	-.9542328	10.00065	.0218069
EuroUSDoll~r	314	.0102378	.000075	.0000859	.0807209	-.0357296	.0449913	.0001048	.191728	5.038654	.0126266
MSCIIntern~s	314	.0294578	.0001723	.0020888	.4057114	-.2381419	.1675696	.0008678	-1.317775	21.42044	.023351
RefinitivG~t	314	.0222353	.0006055	.0024446	.2166376	-.142259	.0743786	.0004944	-1.387338	11.31165	.0248405
RefinitivG~e	314	.025272	.0011814	.0027937	.2453752	-.1395704	.1058048	.0006387	-.9124633	10.41934	.0224451
SPDRFTSEIn~r	314	.0160459	-.0007195	.0003736	.1738324	-.1052195	.0686128	.0002575	-1.169428	11.69447	.0155903
SPGlobalDe~B	314	.0049615	-.0004328	.0000138	.0357305	-.0193783	.0163522	.0000246	-.2553649	4.601015	.0053743
GoldUSD	314	.0192816	.0015431	.00267	.1880852	-.0977228	.0903624	.0003718	-.2271844	6.393262	.0202906
FTSEEPRANa~c	314	.0298154	-.0002246	.0009861	.3708696	-.2249265	.1459431	.000889	-1.839502	20.61085	.0217576
InvescoEme~i	314	.0208404	-.0012079	0	.2667889	-.1739026	.0928863	.0004343	-2.507399	24.44192	.0140083
UKPoundSte~S	314	.0132841	-.0000437	.0004205	.1245503	-.0601887	.0643616	.0001765	-.1726312	6.389581	.0169169
USDollarJa~R	314	.0108146	.0003894	.0010073	.0837528	-.0546776	.0290752	.000117	-.5695426	5.291231	.0123705
BitcoinUSD	314	.1135746	.0091596	.0075854	.7935719	-.5082073	.2853646	.0128992	-.5488779	5.036755	.1241949
EthereumUSD	314	.1541818	.016101	.0122573	1.145527	-.6264855	.5190415	.023772	-.237385	4.86718	.1570537
LitecoinUSD	314	.1611191	.0090718	.0045767	1.263937	-.5735211	.690416	.0259593	.4347323	5.517718	.1437914
US10YearsT~e	314	.068177	.0011992	-.001537	.7241252	-.4102342	.313891	.0046481	-.2698413	9.788989	.0641107
OwnPortfolio	314	.0230424	.0008116	.0019576	.2431873	-.1521535	.0910338	.000531	-1.627001	13.64444	.0220889
MSCIIntern~I	314	.0251373	.001319	.00274	.237169	-.1329938	.1041751	.0006319	-.9077137	10.03897	.021843

Table 1: Descriptive statistics

Cryptocurrencies have on average the highest mean, with Gold/usd (0.015) in second place as a non-crypto asset. This shows that cryptocurrencies have on average had the highest weekly return with respectfully Ethereum (0.0161) as number one, Bitcoin (0.00915) as number two, and then Litecoin (0.009) in the period from 2017 – 2022. This is a significant decline from Parma and Wassvik findings where Ethereum had a weekly return of 0.05425, Bitcoin 0,0311 and Litecoin 0.0205.

	2017-22	2010-17	Absolute Dif	2017-22	2010-17	Absolute dif
Asset	Weekly SD	Weekly SD		Weekly mean	Weekly mean	
MSCIIntern~n	0,0244403			0,001213		
EuroUSDoll~r	0,0102378	0,01362507	-0,0033873	0,000075	-0,000463422	0,000538422
MSCIIntern~s	0,0294578	0,0200059	0,0094519	0,0001723	0,001121846	-0,000949546
RefinitivG~t	0,0222353	0,02022881	0,00200649	0,0006055	0,000283874	0,000321626
RefinitivG~e	0,025272	0,01934799	0,00592401	0,0011814	0,001242791	-6,13909E-05
SPDRFTSEIn~r	0,0160459	0,01213777	0,00390813	-0,0007195	7,02258E-05	-0,000789726
SPGlobalDe~B	0,0049615	0,00320926	0,00175224	-0,0004328	0,000112926	-0,000545726
GoldUSD	0,0192816	0,02260799	-0,0033264	0,0015431	0,000346537	0,001196563
FTSEEPRANa~c	0,0298154	0,0211799	0,0086355	-0,0002246	0,000975603	-0,001200203
InvescoEme~i	0,0208404	0,01110114	0,00973926	-0,0012079	0,000349859	-0,001557759
UKPoundSte~S	0,0132841	0,01190696	0,00137714	-0,0000437	-0,000425944	0,000382244
USDollarJa~R	0,0108146	0,01363808	-0,0028235	0,0003894	0,00051116	-0,00012176
BitcoinUSD	0,1135746	0,16406128	-0,0504867	0,0091596	0,031153265	-0,021993665
EthereumUSD	0,1541818	0,19512916	-0,0409474	0,016101	0,054259932	-0,038158932
LitecoinUSD	0,1611191	0,19242352	-0,0313044	0,0090718	0,020573551	-0,011501751
US10YearsT~e	0,068177			0,0011992		
OwnPortfolio	0,0230424			0,0008116		
MSCIIntern~l	0,0251373	0,01939901	0,00573829	0,001319	0,001409793	-9,07929E-05

Table 2: weekly means and standard deviations:

After comparing our findings with those of Parma and Wassvik (2010-2017), we observe that, on average, eleven assets exhibit lower weekly returns, including cryptocurrencies, while five assets demonstrate a higher standard deviation showcased by the absolute difference. This suggests a more uncertain market during the time period of 2017-2022. It is worth noting that all cryptocurrencies exhibited a higher standard deviation during the time period of 2010-2017, as indicated by Parma and Wassvik. This period was characterized by extreme price growth. In this case, the presence of extreme positive outliers above the mean contributed to a higher standard deviation than what we observed in our own findings from 2017-2022. While our dataset also featured outliers above and below the mean, they were not as extreme as those in Parma and Wassvik's dataset. Therefore, we can argue that our calculated variance and standard deviation (risk) provide a more representative measure for the cryptocurrencies in question.

We also observe that the MSCI International World Price Index performed worse during the 2017-2022 period compared to the 2010-2017 timeframe, as found by Parma and Wassvik. It exhibited lower returns and higher risk. However, within our dataset, the MSCI International World Price Index outperformed our constructed market portfolio, with a higher weekly return of 0.0013. Nevertheless, it also had a higher standard deviation of 0.02513. Apart from cryptocurrencies and gold, the MSCI International World Price Index displayed a better weekly return than all other assets. When we compare returns with risk, we once again notice that only a few assets managed to outperform the market, consistent with the findings of Parma and Wassvik. This suggests that the MSCI International World Price Index performed better than our constructed market portfolio, which aimed to reflect the average investment opportunities for cryptocurrency investors.

Minimum and maximum show the lowest and highest weekly return. From table 1, we can see that cryptocurrencies have had the highest observations with Litecoin (0.69) followed by Ethereum (0.519) and bitcoin at (0.28). Cryptocurrencies have also had the lowest weekly return with Ethereum (-0.62), Litecoin (-0.57) and Bitcoin (-0.5) also giving cryptocurrencies the highest observed range. S&P Global Developed Sovereign Bond Index is the asset with lowest range (0.035) with the highest observation at 0.016 and lowest at -0.019.

Our two market portfolios, the self-constructed portfolio and MSCI International World Price Index, have a range of 0.24 and 0.23, with the highest observed values of 0.09 and 0.1 and lowest observed values of -0.15 and -0.13.

Based on our descriptive statistics, we have found that cryptocurrencies have the highest average weekly return, highest standard deviation, as well as the highest and lowest observations. These findings align with those of Parma and Wassvik (2010-2017). However, our data set reveals a significant decrease in weekly returns except for Gold/USD and an increase in standard deviation for most assets compared to their findings. Additionally, our descriptive statistics indicate that only a few assets manage to outperform our two market portfolios, with the MSCI International World Price Index slightly surpassing our own constructed portfolio designed to represent the average investment opportunities for cryptocurrency traders. This suggests cryptocurrencies yield a higher return for the average crypto investor.

5.4 Skewness

Looking at the skewed values from the descriptive statistics we can see that the skewness of most of the assets is negative, indicating a longer left tail, or a distribution that is skewed to the left. This means most of the observations are concentrated on the right side of the distribution graph with some outliers to the left of the mean (Taylor, 2023). This also includes the cryptocurrencies Bitcoin and Ethereum with -0.5489 and -0.2374, indicating that an investor in the period from 2017-2022 could expect small gains and some bigger losses.

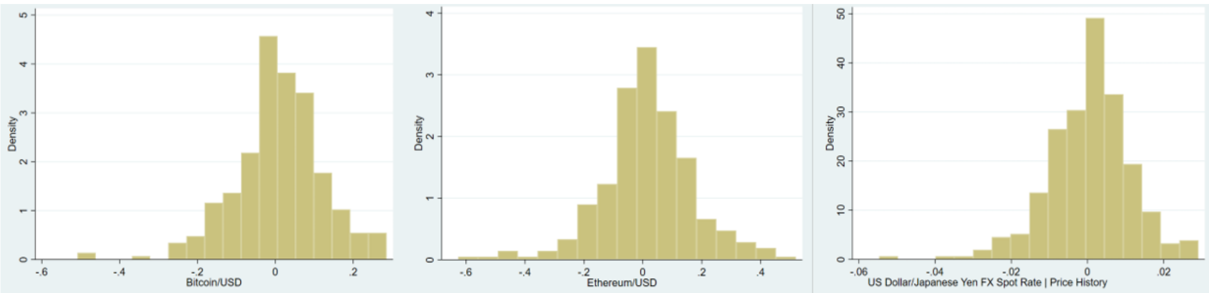


Figure 6: Histogram (Bitcoin, Ethereum, USD/YEN)

Looking at the histogram for Bitcoin, Ethereum and US Dollar/Japanese Yen we can clearly see observations skewing the distribution to the left.

Litecoin (0.43) and Euro/USD (0.19) were the only assets with positive skewness, indicating distributions that are skewed to the right, this might indicate that an investor could have experienced small losses and some higher gains. (Chen, 2023)

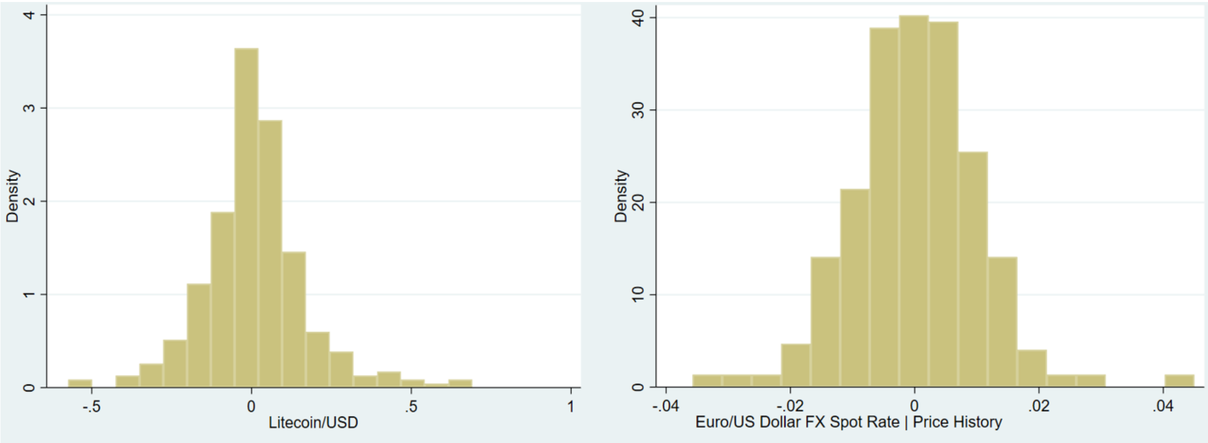


Figure 7: Histogram (Litecoin, Euro/USD)

When examination the histogram for Litecoin and Euro/US dollar we can see some observations to the right of the mean (outliers) making the distribution skewed to the right.

Asset	2010-2017	2017-2022
BTC.USD.rate	0,1729158	-0,5488779
LTC.USD.rate	2,0646879	0,4347323
ETH.USD.rate	0,5546736	-0,2373850

Table 3: Skewness 2010-2017, 2017-2022 comparison

When we compare the skewness from Parma and Wassvik (2010-2017), we can see that both Bitcoin and Ethereum went from a positive skewness to a negative skewness. This means that the distribution of the returns went from extreme positive returns to more extreme negative returns. Litecoin still has a distribution skewed to the right but with less extreme returns (outliers).

5.5 Kurtosis

Going back to table 1 “Descriptive statistics”, we see that the kurtosis values for the crypto currencies (Bitcoin, Ethereum, Litecoin) are higher than 3, indicating that their returns distribution are more peaked than a normal distribution and are associated with higher level of risk (Kenton, 2023). In general, all assets have a kurtosis higher than 3, indicating a higher risk than observed in Parma-Wassvik findings and not normally distributed. We will explore this further in the next section.

5.6 Testing for normality.

Testing for normal distribution in finance is important because many statistical models and theories rely on this assumption. It helps validate the accuracy of these models and identifies potential risks or deviations from normality (Chen, 2023). We have used the skewness, kurtosis and Shapiro-Wilk W test for normality.

5.6.1 Skewness and kurtosis test for normality

We conducted a skewness and kurtosis test for normality using the "Sktest" in Stata. "sktest presents a test for normality based on skewness and another based on kurtosis and then combines the two tests into an overall test statistic" (Stata, p 1-5)

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test Adj chi2(2)	Joint test Prob>chi2
MSCIInternationalACWIPriceIn	314	0.0000	0.0000	68.44	0.0000
EuroUSDollarFXSpotRatePr	314	0.1596	0.0000	17.14	0.0002
MSCIInternationalWorldRealEs	314	0.0000	0.0000	110.81	0.0000
RefinitivGlobalEmergingMarket	314	0.0000	0.0000	91.83	0.0000
RefinitivGlobalDevelopedPrice	314	0.0000	0.0000	68.18	0.0000
SPDRFTSEIntlGovtInflationPr	314	0.0000	0.0000	83.49	0.0000
SPGlobalDevelopedSovereignB	314	0.0627	0.0002	14.93	0.0006
GoldUSD	314	0.0967	0.0000	26.81	0.0000
FTSEEPRANareitGlobalEURPric	314	0.0000	0.0000	131.90	0.0000
InvescoEmergingMarketsSoverei	314	0.0000	0.0000	163.93	0.0000
UKPoundSterlingUSDollarFXS	314	0.2047	0.0000	25.94	0.0000
USDollarJapaneseYenFXSpotR	314	0.0001	0.0000	29.08	0.0000
BitcoinUSD	314	0.0001	0.0000	26.53	0.0000
EthereumUSD	314	0.0829	0.0000	16.63	0.0002
LitecoinUSD	314	0.0020	0.0000	26.20	0.0000
US10YearsTreasuryNote	314	0.0496	0.0000	43.90	0.0000
OwnPortfolio	314	0.0000	0.0000	108.90	0.0000
MSCIInternationalWorldPriceI	314	0.0000	0.0000	66.61	0.0000

Table 4: Skewness and kurtosis test for normality

As seen in table 4, all assets have a p value less than the critical value of 0.05, meaning we reject the null hypothesis that the assets are normally distributed with a less than 5% change to conduct a type 1 error.

5.6.2 Shapiro-Wilk W test for normality

The Shapiro-Wilk W test for normality confirms the findings we found in our skewness and kurtosis test for normality (table 4), as all p-values are less than 0.05, we reject the null hypothesis that our data in our research are normally distributed.

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
MSCIIntern~n	314	0.89799	22.630	7.338	0.00000
EuroUSDoll~r	314	0.97763	4.964	3.769	0.00008
MSCIIntern~s	314	0.80600	43.039	8.850	0.00000
RefinitivG~t	314	0.90221	21.695	7.239	0.00000
RefinitivG~e	314	0.89163	24.041	7.480	0.00000
SPDRFTSEIn~r	314	0.89584	23.108	7.387	0.00000
SPGlobalDe~B	314	0.97103	6.426	4.377	0.00001
GoldUSD	314	0.96490	7.787	4.828	0.00000
FTSEEPRANa~c	314	0.78921	46.763	9.046	0.00000
InvescoEme~i	314	0.76137	52.940	9.337	0.00000
UKPoundSte~S	314	0.95965	8.952	5.156	0.00000
USDollarJa~R	314	0.97181	6.254	4.312	0.00001
BitcoinUSD	314	0.97013	6.627	4.449	0.00000
EthereumUSD	314	0.97181	6.253	4.312	0.00001
LitecoinUSD	314	0.95764	9.398	5.271	0.00000
US10YearsT~e	314	0.90688	20.658	7.124	0.00000
OwnPortfolio	314	0.86763	29.366	7.951	0.00000
MSCIIntern~I	314	0.89440	23.428	7.420	0.00000

Table 5: Shapiro-Wilk W test for normality

Given the results in descriptive statistics from skewness, kurtosis, visualizing the distribution in histograms, the skewness and kurtosis test for normality and the Shapiro-Wilk W test, we can conclude that none of our assets are following a normal distribution. These findings align with those of Parma and Wassvik (2010-2017).

5.7 Correlation Matrix

The correlation matrix (table6) shows that cryptocurrencies have a strong correlation between each other. Bitcoin/Ethereum 0.699, Bitcoin/Litecoin 0.73, Ethereum/Litecoin 0.69 and a weak to negative correlation with other non-cryptocurrencies assets. Note that Ethereum and Litecoin correlate stronger with Bitcoin than with each other, indicating that cryptocurrencies might follow Bitcoins price movement. Our two market portfolios, MSCI international world price index and our own portfolio, show a strong correlation of 0.95 indicating that both indexes might have similar asset allocations and shared exposure to certain industries and sectors.

```
. corr
(obs=314)
```

	MSCIIn~n	EuroUS~r	MSCIIn~s	Refini~t	Refini~e	SPDRFT~r	SPGlob~B	GoldUSD	FTSEEP~c	Invesc~i	UKPoun~S	USDoll~R	Bitcoi~D	Ethere~D	Liteco~D	US10Ye~e	OwnPor~o	MSCIIn~I
MSCIIntern~n	1.0000																	
EuroUSDoll~r	-0.0486	1.0000																
MSCIIntern~s	0.8215	-0.0937	1.0000															
RefinitivG~t	0.8184	0.0284	0.6726	1.0000														
RefinitivG~e	0.9976	-0.0692	0.8273	0.7991	1.0000													
SPDRFTSEIn~r	0.6348	-0.0977	0.7038	0.5975	0.6382	1.0000												
SPGlobalDe~B	0.0739	0.0031	0.2390	-0.0063	0.0765	0.4629	1.0000											
GoldUSD	0.2974	-0.1523	0.3619	0.3349	0.2977	0.5601	0.3459	1.0000										
FTSEEPRANa~c	0.7986	-0.1681	0.9106	0.7472	0.8057	0.7069	0.2069	0.4236	1.0000									
InvescoEme~i	0.7044	-0.0391	0.7269	0.6618	0.7088	0.6839	0.3709	0.4295	0.7508	1.0000								
UKPoundSte~S	0.0028	0.6870	-0.0276	0.0690	-0.0137	-0.0630	-0.0244	-0.1668	-0.0711	0.0237	1.0000							
USDollarJa~R	-0.1056	0.1159	-0.2198	-0.1457	-0.1078	-0.4851	-0.4996	-0.5090	-0.2472	-0.3350	0.1386	1.0000						
BitcoinUSD	0.2579	-0.0265	0.1352	0.2496	0.2560	0.1989	0.0571	0.1460	0.1773	0.1941	-0.0401	-0.0504	1.0000					
EthereumUSD	0.3240	0.0254	0.1963	0.2980	0.3222	0.2397	0.0515	0.1545	0.2113	0.2371	-0.0066	-0.0864	0.6999	1.0000				
LitecoinUSD	0.2599	-0.0391	0.1542	0.2456	0.2573	0.1797	0.0126	0.1349	0.1716	0.1880	-0.0245	-0.0459	0.7324	0.6943	1.0000			
US10YearsT~e	0.1535	0.0292	0.0234	0.1952	0.1551	-0.2327	-0.7816	-0.3544	0.0173	-0.1694	0.0879	0.4743	-0.0154	-0.0146	0.0092	1.0000		
OwnPortfolio	0.9552	-0.0300	0.7830	0.8659	0.9496	0.6426	0.0505	0.3586	0.7895	0.7065	0.0162	-0.1122	0.2822	0.3321	0.2809	0.1652	1.0000	
MSCIIntern~I	0.9967	-0.0609	0.8267	0.7790	0.9976	0.6277	0.0783	0.2816	0.7928	0.6990	-0.0042	-0.0948	0.2543	0.3208	0.2574	0.1508	0.9444	1.0000

Table 6: Correlation matrix

5.8 Annualized return

Table 7 displays the yearly arithmetic mean and yearly geometric mean returns for the assets in our dataset (2017-2022).

Asset	Arithmetic mean	Geometric mean
	Average yearly return	Average Yearly return
MSCI Internation	0,065107784	0,048457462
Euro/US Dollar F	0,003907615	0,001196715
MSCI Internation	0,008984117	-0,014234123
Refinitiv Global I	0,031960096	0,018525507
Refinitiv Global I	0,063336919	0,045626262
SPDR FTSE Intl G	-0,036722744	-0,043227464
S&P Global Deve	-0,022254238	-0,022874323
Gold/USD	0,083542754	0,073113246
FTSE EPRA Narei	-0,011611263	-0,035168689
Invesco Emergin	-0,060878861	-0,071826683
UK Pound Sterlin	-0,00226982	-0,006830168
US Dollar/Japan	0,020433972	0,01736098
Bitcoin/USD	0,610138178	0,125523207
Ethereum/USD	1,310010338	0,190603117
Litecoin/USD	0,602787018	-0,187471916
US 10 Years Tre	0,064332668	-0,060639543
Own Portfolio	0,043128113	0,028477959
MSCI Internation	0,070994868	0,053320968

Table 7:Annualized return

One notable finding is that the geometric mean return for cryptocurrencies such as Bitcoin, Ethereum, and Litecoin is significantly lower than the arithmetic mean return. For instance, Bitcoin has an arithmetic mean return of 61.0% and a geometric mean return of 12.6%, while Ethereum has an arithmetic mean return of 131.0% and a geometric mean return of 19.1%. Similarly, Litecoin has an arithmetic mean return of 60.3% but a negative geometric mean return of -18.7%.

The difference between the two types of means can be explained by the high volatility and unpredictability of the cryptocurrency market. While cryptocurrencies may experience periods of high returns, they may also experience significant losses, which can have a significant impact on the overall performance. This is reflected in the lower geometric mean return as it accounts for the compounding effect of these fluctuations.

However, despite the differences in arithmetic and geometric mean, Bitcoin and Ethereum have on average shown a superior yearly arithmetic and geometric mean return compared to the rest of the assets in our dataset.

Asset	Geometric mean	Arithmetic mean
BTC.USD.rate	1,361206329	1,619969796
LTC.USD.rate	0,271189954	1,069824652
ETH.USD.rate	5,492198485	2,821516475
Gold.US.Dollar.FX.Spot.Rate	0,004709896	0,018019913
MSCI.International.World.Price.Index.USD.Realtime	0,065483864	0,073309233

Table 8: Geometric&Arithmetic mean (yearly) Parma-Wassvik

Comparing the arithmetic and geometric mean for cryptocurrencies with Parma and Wassvik findings, we observed a dramatic decrease in average return in our dataset. Ethereum went from a geometric yearly return of 549% to 19% and from an arithmetic yearly mean of 282% to 131%. Bitcoin went from a geometric yearly return of 136% to 12.5% and from an arithmetic yearly mean of 161% to 61%. Litecoin went from a geometric yearly return of 27% to -18 % and from an arithmetic yearly mean of 106 % to 60%. (Parma-Wassvik)

It is also worth noting that the MSCI International World Price Index USD has an arithmetic mean return of 7.1% and a geometric mean return of 5.3%. In comparison, the arithmetic mean returns for Own portfolio is 4.3% and a geometric mean return of 2%, meaning MSCI shows on average a high return of those two market portfolios.

In Parma and Wassvik, the MSCI international World Price Index showed an arithmetic mean return of 7.3%, and a geometric mean return of 6.5%, generating on average the highest return as a non-crypto asset. In our results, as the non-crypto asset we see that Gold/USD has the highest return for both arithmetic (8.3%) and geometric (7.3%) mean Gold/USD outperforms both of our two market portfolios. Comparing the average yearly return of gold with Parma-Wassvik, we can see a significant increase in return for both the arithmetic and geometric mean in our dataset.

Other notable findings from Table 7 are that assets from our dataset range from -6.1% to 6.4%, while the geometric mean returns range from -0.7% to 4.8%.

5.9 CAPM and beta

In table 9 we see 4 betas with the corresponding yearly expected return based on the assets systematic risk compared to our two market portfolios, MSCI international world price index and Own constructed portfolio, computed by the capital asset pricing model (CAPM).

Asset	MSCI		Own portfolio		CAPM (yearly) (2017-2022)	
	Beta COV/VAR	BETA KORR/STD	Beta COV/VAR	Beta KORR/STD	MSCI	Own
MSCI International ACWI Price In	0,965807011	0,968902546	1,00949004	1,012725585	0,069764096	0,042850189
Euro/US Dollar FX Spot Rate | Pri	-0,025451035	-0,025532608	-0,013969841	-0,014014616	0,034083893	0,034793131
MSCI International World Real Es	0,965232961	0,968326657	0,997198572	1,000394721	0,069743433	0,042845523
Refinitiv Global Emerging Market	0,687017199	0,689219177	0,832993102	0,835662951	0,059729094	0,040584154
Refinitiv Global Developed Price F	0,999630566	1,00283451	1,037864519	1,041191008	0,070981571	0,04312511
SPDR FTSE Intl Govt Inflation-Pro	0,399315284	0,40059514	0,445870891	0,447299965	0,049373301	0,03824568
S&P Global Developed Sovereign	0,014099925	0,014145117	0,009602568	0,009633345	0,035507525	0,035114606
Gold/USD	0,213752059	0,214437161	0,297698815	0,298652978	0,042693977	0,036737401
FTSE EPRA Nareit Global EUR Pric	0,938555845	0,941564036	1,019350421	1,02261757	0,068783194	0,042628688
Invesco Emerging Markets Sovere	0,575435789	0,577280135	0,634717976	0,636752329	0,055712735	0,039677207
UK Pound Sterling/US Dollar FX Sp	-0,002586059	-0,002594348	0,008983542	0,009012336	0,034906915	0,03497898
US Dollar/Japanese Yen FX Spot F	-0,04128224	-0,041414555	-0,053100433	-0,053270626	0,033514051	0,034664453
Bitcoin/USD	1,145923492	1,149596324	1,386917407	1,391362655	0,076247365	0,044314196
Ethereum/USD	1,961111187	1,9673968	2,214512828	2,221610626	0,105589939	0,050940134
Litecoin/USD	1,641281201	1,646541718	1,954672491	1,960937467	0,094077701	0,04834052
US 10 Years Treasury Note	0,415489167	0,416820863	0,494506058	0,496091014	0,049955478	0,038377143
Own Portfolio	0,863001096	0,865767125	0,996805112	1	0,066063611	0,042014571
MSCI International World Price In	0,996805112	1	1,026692659	1,02998334	0,070879869	0,043102145

Risk free (yearly)	0,035
e(rm) MSCI yearly	0,070994868
e(rm) Own yearly	0,043128113

Table 9: CAPM and beta

The betas have been calculated using the following methods,

Covariance/Variance method:

$$Beta = \frac{Covariance\ (R_i, R_m)}{Variance\ (R_m)}$$

Correlation method

$$Beta = \sum Correlation\ (R_i, R_m) * \frac{\sigma_i}{\sigma_m}$$

(Mahey, 2023)

As seen by the formulas, the covariance/variance method calculates beta by dividing the covariance of the asset's returns with the market returns by the variance of the market returns. On the other hand, the correlation/standard deviation method calculates beta by dividing the correlation coefficient between the asset's returns and the market returns by the standard deviation of the market returns.

According to "Christoffersen, P. (2012). Elements of Financial Risk Management (2nd ed.). Academic Press», when returns are not normally distributed, we should use the correlation method to estimate the betas. As seen in chapter 5.6, we have already rejected the null hypothesis of normal distributed returns, we therefore used the beta from the covariance/variance method in estimating the assets expected returns (CAPM). As we use the beta calculated by covariance/variance in the CAPM, it is natural to proceed with and discuss this beta further. Parma-Wassvik proceeded with the same beta and there is only a slight difference between the two beta values as seen in table 9. It is also important to inform that we will proceed with the Beta calculated used MSCI international world price index as benchmark when comparing to Parma-Wassvik's findings. This is to obtain the best possible basis for comparison.

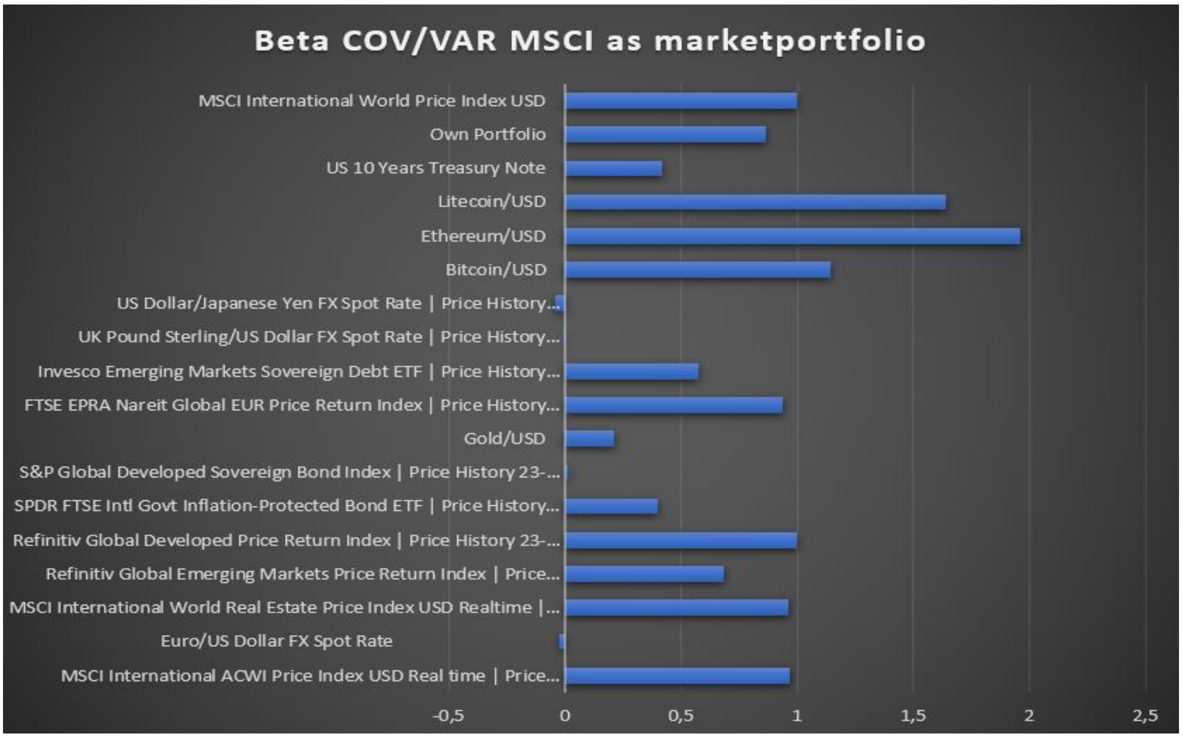


Figure 8: Beta cov/var with MSCI as benchmark

Assuming that the MSCI international world price index (market portfolio) is efficient, meaning all unsystematic risk (firm specific) is gone and it cannot be diversified more without lowering expected return, and is therefore only reacting to changes in systematic risk, the market portfolio will have a beta of 1. Using this as a benchmark, we can calculate the expected percentage changes in assets return given a 1% change in the market portfolio due to systemic shock (beta). (Berk and DeMarzo, 2020, p 379).

Looking at table 9, we see that Bitcoin (1.145), Ethereum (1.96) and Litecoin (1.64) all have a beta above 1, meaning they are sensitive to systematic risk, or market risk and follows the market. For every percent MSCI international world price index moves, Bitcoin returns will on average move 1.145%, Ethereum returns 1.96% and Litecoin returns 1.64 % in the same direction as the market portfolio because their betas are positive.

An investor needs to be compensated for the risk he is taking and as seen by the capital asset pricing model, cryptocurrencies have the highest required return based on the systematic risk associated by investing in them. An investor will require a 7.6% return for investing in Bitcoin, 10.5% for investing in Ethereum and 9.4% for investing in Litecoin.

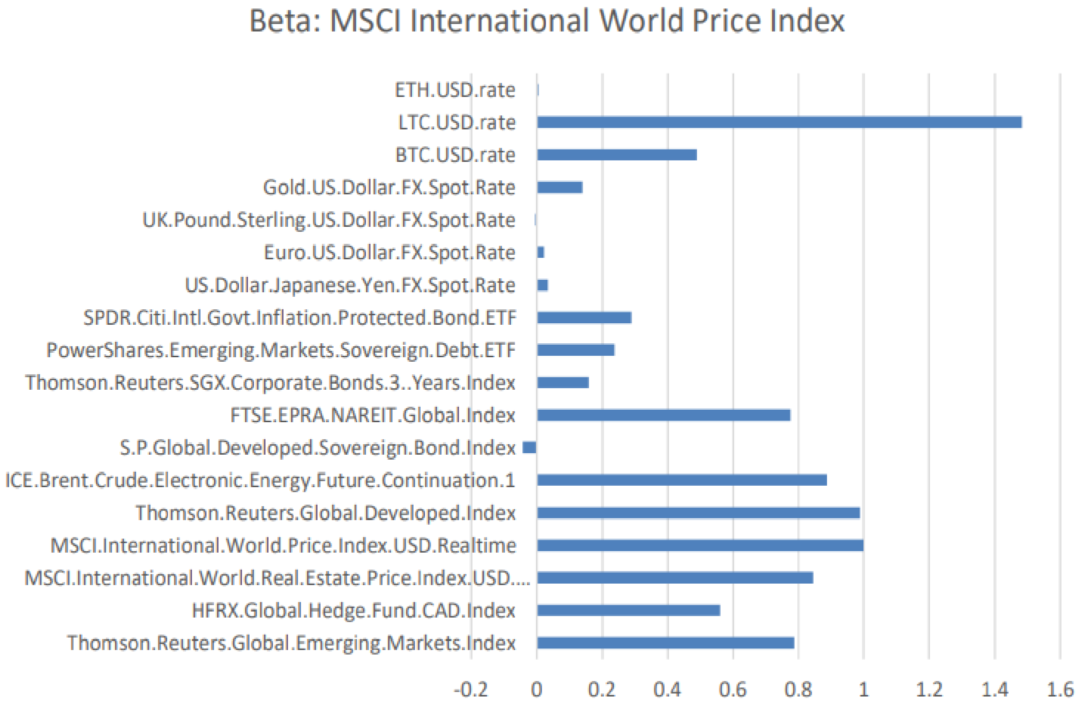


Figure 9: Beta cov/var (Parma-Wassvik)

In comparison to the findings of Parma and Wassvik (figure 9), our study reveals significant changes in betas. From 2017 to 2022, cryptocurrencies exhibited higher market risk compared to the period of 2010 to 2017, indicating that investors during 2017-2022 would generally require a higher return on their investments based on the CAPM. Additionally, we identified three assets in our dataset with negative betas (UK pound/USD, Euro/USD, and USD/Yen), indicating an inverse relationship with the market. Apart from these, the remaining assets in our dataset exhibited betas below 1, suggesting lower exposure to systematic risk compared to the overall market. Similar to Parma and Wassvik, we utilized an annual risk-free rate of 3.5% and set the expected return of the market portfolio to the average yearly return of the MSCI international world price index.

5.10 Jensen's Alpha

We have chosen to focus on the Jensen's Alpha calculated using the covariance/variance beta with MSCI as the market portfolio for better comparison with Parma and Wassviks findings. However, it is wort noticing that for the crypto investor not able to invest in the MSCI International World Price Index, he would have greater access return investing in cryptocurrencies comparing to alternative investments available for him as seen in table 10 under "own yearly marketportfoloi" indicating again that cryptocurrencies might be a good investment for an investor that does not have access to the western market represented by the MSCI International world price index.

Jensens Alpha 2017-2022		
ASSET	(MSCI) yearly	(own) yearly
MSCI International AC	-0,004656312	0,022257596
Euro/US Dollar FX Spo	-0,030176278	-0,030885516
MSCI International Wo	-0,060759316	-0,033861406
Refinitiv Global Emerg	-0,027768997	-0,008624057
Refinitiv Global Develo	-0,007644652	0,020211808
SPDR FTSE Intl Govt In	-0,086096045	-0,074968424
S&P Global Developed	-0,057761763	-0,057368844
Gold/USD	0,040848776	0,046805353
FTSE EPRA Nareit Glob	-0,080394457	-0,054239951
Invesco Emerging Mar	-0,116591597	-0,100556069
UK Pound Sterling/US	-0,037176735	-0,0372488
US Dollar/Japanese Ye	-0,013080079	-0,014230481
Bitcoin/USD	0,533890813	0,565823982
Ethereum/USD	1,204420399	1,259070204
Litecoin/USD	0,508709317	0,554446498
Own Portfolio	-0,022935498	0,001113543
MSCI International Wo	0,000115	0,027892723

Table 10: Jensens Alpha

In Table 10, we observe that four assets exhibit positive Alpha values. These include cryptocurrencies (Ethereum, Bitcoin, and Litecoin) as well as Gold. These assets outperformed the required return calculated by the capital asset pricing model. Among them, Ethereum stands at the top with an Alpha value of 1.204 (120.4%), followed by Bitcoin with 0.53 (53%), Litecoin with 0.5 (50%), and Gold with the lowest positive value of 0.04.

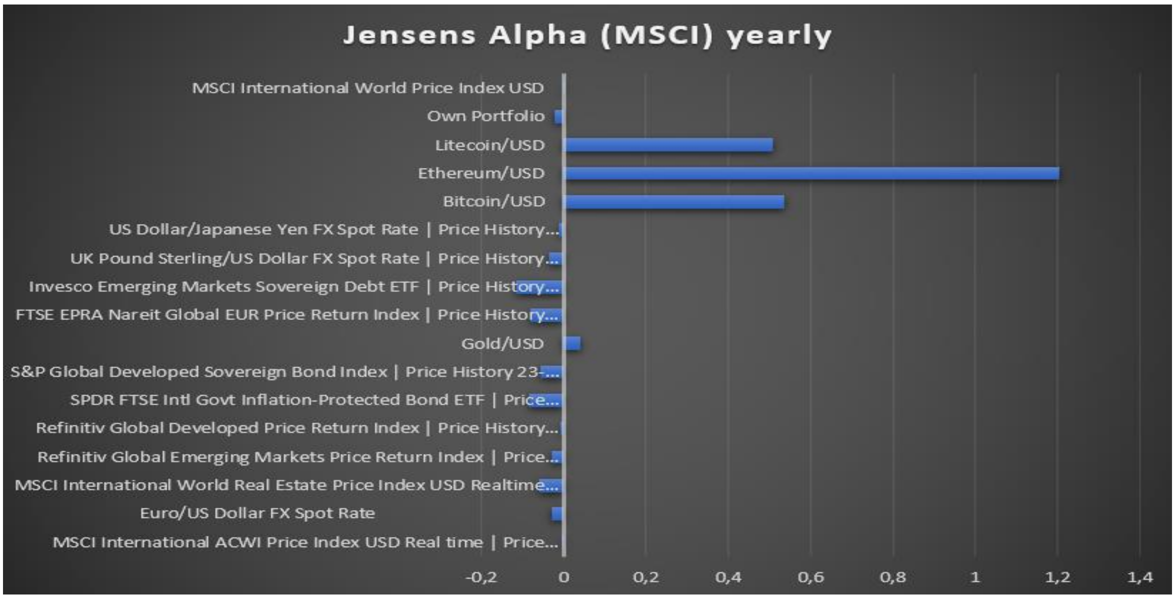


Figure 10: Jensens Alpha with MSCI as bench

The rest of the assets performed poorer than the required return calculated by the capital asset pricing model with Invesco emerging markets sovereign debt ETF at the lowest value of -0.11 (-11%) less than required return.

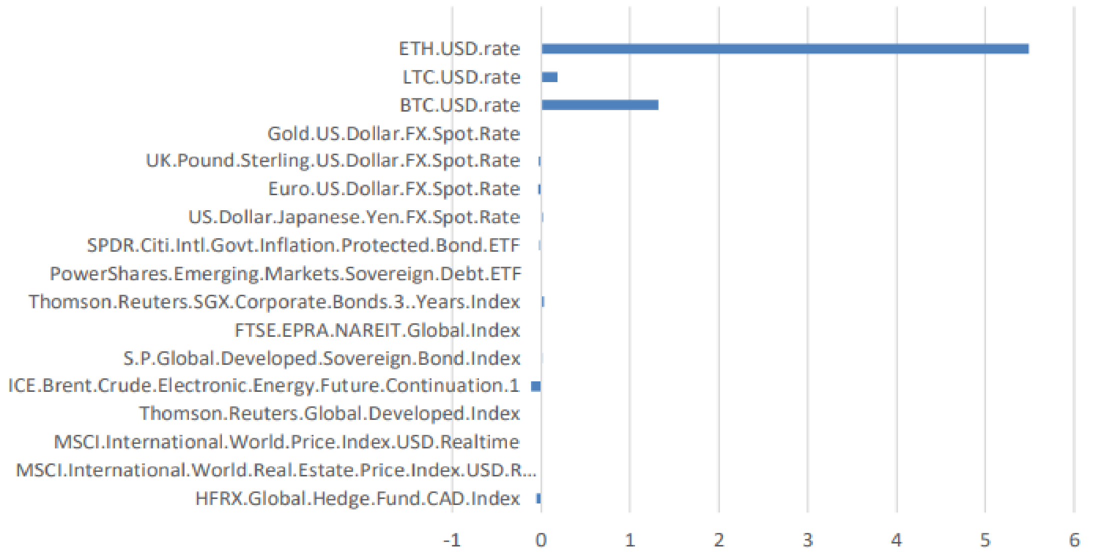


Figure 11: Jensens Alpha (Parma-Wassvik)

When comparing the excess return with Parma-Wassvik (figure 11), we can see that their dataset from 2010-2017 gave a significantly higher Alpha value for Bitcoin 1.32 (132%) and Ethereum 5.49 (549%), but a lower alpha value for Litecoin 0.18 (18%) than in our findings. They also have additional 2 non cryptocurrencies assets beating the excepted return set by the CAPM.

Summing up the results from Jensen’s Alpha for the assets and their dataset, we can see that cryptocurrencies have been a better investment as they have exceeded the required return in the period 2017-2022, however the outperformance has seen a significant decrease from the period 2010 – 2017 (Parma-Wassvik).

5.11 Treynor ratio

From table 11 and figure 12, we see that the S&P Global Developed Sovereign Bond Index has the highest Treynor ratio at 2.54, indicating that it has the highest excess return per unit of systematic risk. On the other hand, the UK Pound Sterling/US Dollar FX Spot Rate has the lowest Treynor ratio, indicating that it is providing a negative excess return per unit of systematic risk.

Treynor ratio	
ASSET	Value based on (MSCI)
MSCI International ACW	0,037150143
Euro/US Dollar FX Spot R	-1,409760721
MSCI International Worl	0,037172237
Refinitiv Global Emergin	0,052225576
Refinitiv Global Develop	0,035893129
SPDR FTSE Intl Govt Infla	0,089853482
S&P Global Developed S	2,544685154
Gold/USD	0,167857419
FTSE EPRA Nareit Global	0,038228805
Invesco Emerging Marke	0,062352515
UK Pound Sterling/US Do	-13,87434258
US Dollar/Japanese Yen	-0,869135707
Bitcoin/USD	0,031310876
Ethereum/USD	0,018295683
Litecoin/USD	0,021860891
US 10 Years Treasury No	0,086355726
Own Portfolio	0,041575693
MSCI International Worl	0,035994868

Table 11: Treynor ratio

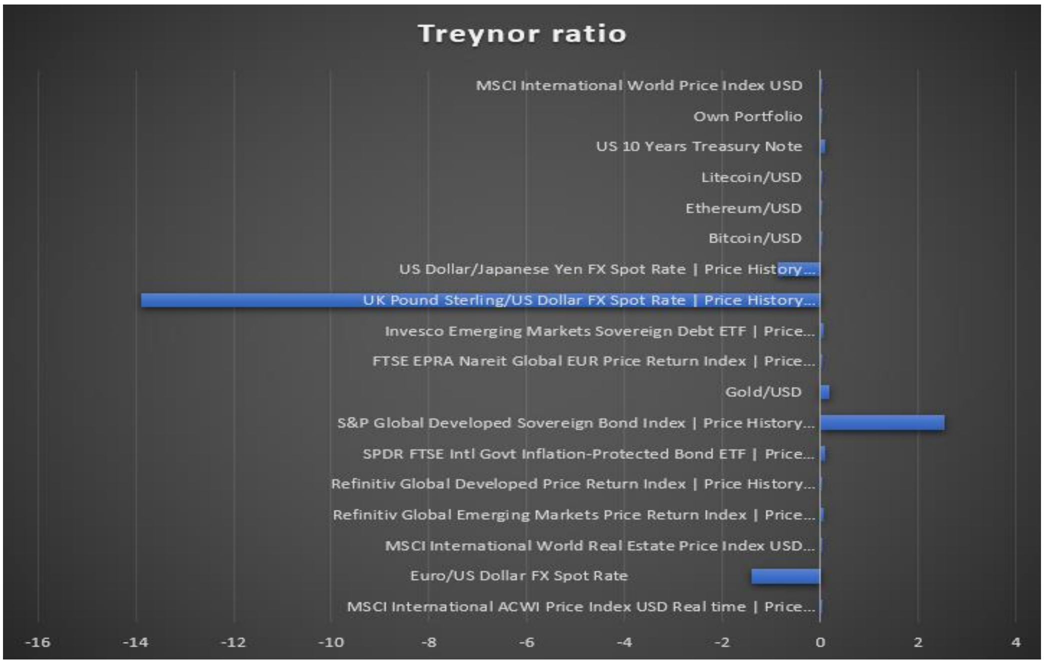


Figure 12: Traynor ratio

Regarding cryptocurrencies, Bitcoin has a Treynor ratio of 0.031, indicating that it is providing a positive excess return for the amount of systematic risk it possesses. Ethereum and Litecoin have lower Treynor ratios of 0.018 and 0.0218 respectively, indicating that they are providing lower excess returns per unit of systematic risk compared to Bitcoin.

MSCI International World Price Index USD, which represents the market portfolio, has a Treynor ratio of 0.0035. This means that the market portfolio is providing a relatively low excess return for the systematic risk it possesses, compared to other assets in the table.

When comparing the assets' Treynor ratios from the different time periods (figure 13), we observe that the Treynor ratio for Bitcoin decreased significantly from 2.624671 (2010-2017) to 0.03131 (2017-2022), Litecoin's Treynor ratio decreased from 0.153523 to 0.021, while Ethereum's Treynor ratio decreased from dramatically 1143.524 to 0.0182 indicating a decline in the excess return per unit of systematic risk compared to Parma and Wassvik's findings.

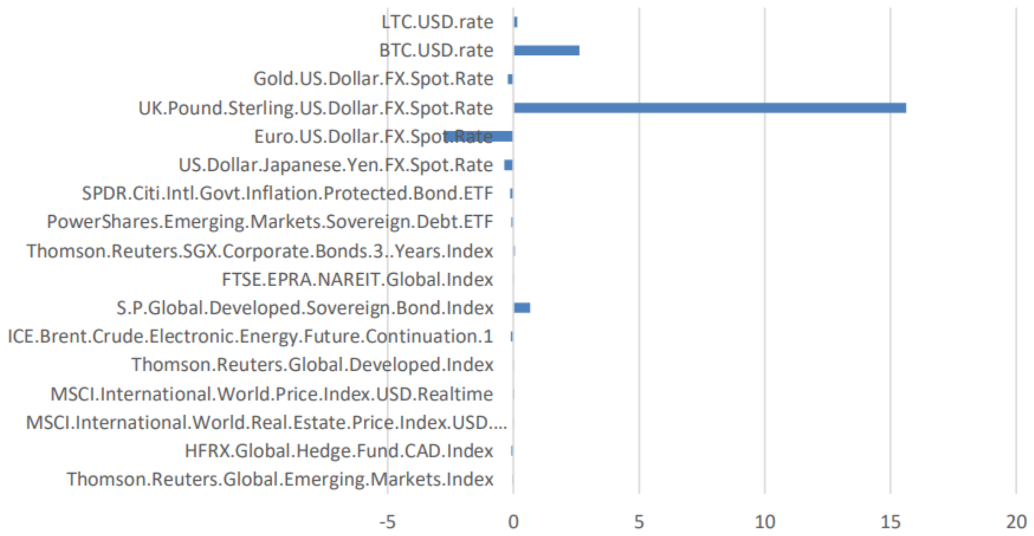


Figure 13: Treynor ratio (Parma-Wassvik)

However, despite the decrease in Treynor ratios for cryptocurrencies, our findings indicate that cryptocurrencies have proven to be a favorable investment asset during the period of 2017-2022 compared to other assets in our dataset, as evidenced by their strong Treynor ratios.

5.12 Information ratio

Looking at the data from table 12 and figur14, we can see that Bitcoin, Ethereum, Litecoin and gold as the only non-crypto asset, have positive information ratios, meaning they have outperformed the benchmark MSCI International World Price Index USD on a risk-adjusted basis.

Information ratio (2017-2022)		
ASSET	MSCI based values	Own portfolio
MSCI International A(	-0,049972632	0,055436333
Euro/US Dollar FX Sp(	-0,044887871	-0,028894906
MSCI International W	-0,069097435	-0,034890021
Refinitiv Global Emer	-0,044640221	-0,01754355
Refinitiv Global Devel	-0,078379649	0,046359223
SPDR FTSE Intl Govt I	-0,10416907	-0,086510359
S&P Global Develope	-0,069407818	-0,053351556
Gold/USD	0,008292096	0,030267949
FTSE EPRA Nareit Glo	-0,084652305	-0,056610942
Invesco Emerging Ma	-0,138304314	-0,119263017
UK Pound Sterling/US	-0,047844355	-0,032385163
US Dollar/Japanese Y	-0,032857884	-0,015915044
Bitcoin/USD	0,071341034	0,076355981
Ethereum/USD	0,099849017	0,103214636
Litecoin/USD	0,04952434	0,052875137
US 10 Years Treasury	-0,001734982	0,005678012
Own Portfolio	-0,061151184	#DIV/0!
MSCI International W	#DIV/0!	0,061151184

Table 12: Information ratio

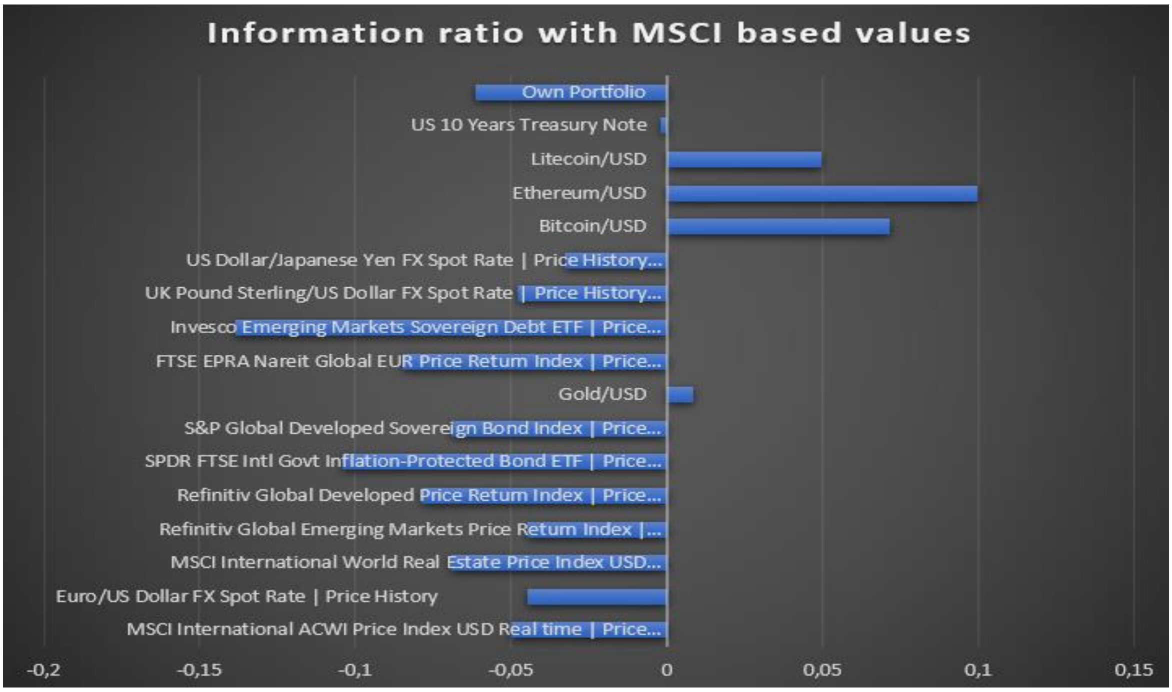


Figure 14: Information ratio with MSCI based values.

Ethereum has the highest information ratio among all assets (0.09), indicating that it has delivered the best risk-adjusted performance. Again, we only showcase values based on MSCI International world price index for comparing our results to Parma-Wassviks findings.

The other assets have negative information ratios, implying that they have underperformed their benchmark on a risk-adjusted basis. This finding shows that cryptocurrencies and gold have been a good asset to invest in during 2017-2022.

However, when we compare the information ratios of cryptocurrencies with the findings of Parma-Wassvik (figure 15), we can see that Ethereum's ratio decreased from 3.8 to 0.099, Bitcoin's ratio went down from 1.08 to 0.071, and Litecoin's ratio dropped from 0.15 to 0.049. This suggests that cryptocurrencies may have been a better investment option during the period between 2010 and 2017, based on their higher information ratios.

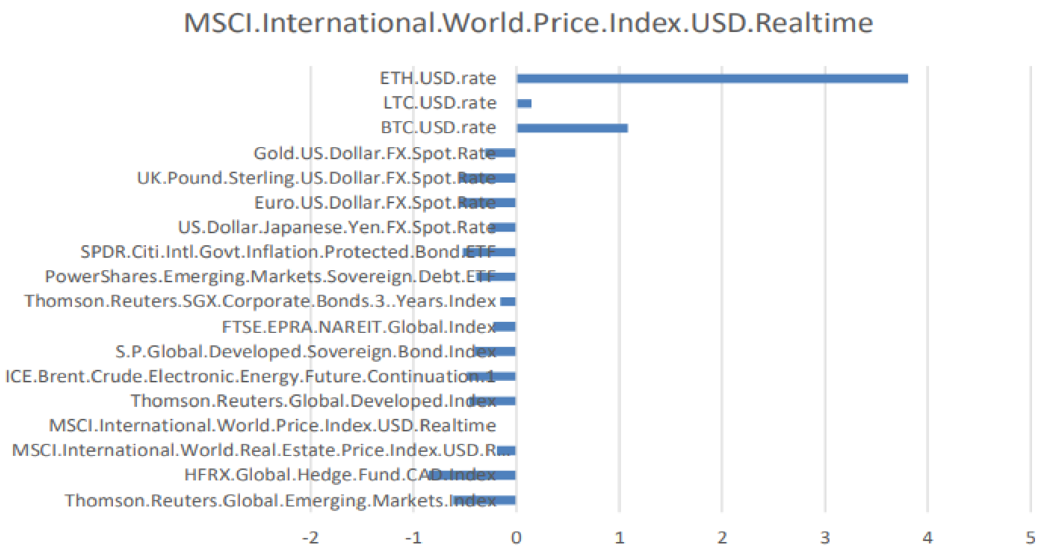


Figure 15: Information ratio (Parma-Wassvik)

despite the decrease in information ratios for cryptocurrencies, our findings indicate that cryptocurrencies (and Gold/USD) have proven to be a favorable investment asset during the period of 2017-2022 compared to other assets in our dataset, as evidenced by their high information ratios

5.13 Sharpe ratio

Table 13 and figure 16 presents the annualized Sharpe ratios for all the assets in our dataset. The table reveals that half of the assets have positive Sharpe ratios, while the other half has negative Sharpe ratios. Negative Sharpe ratios can arise when the returns are negative or when the annual return is lower than our annual risk-free rate of 3.5%.

Asset	Sharpe annualized
MSCI International ACWI	0,022553544
Euro/US Dollar FX Spot R	-0,057315559
MSCI International Worl	-0,016626662
Refinitiv Global Emerging	-0,002553816
Refinitiv Global Develope	0,020545061
SPDR FTSE Intl Govt Infla	-0,086083383
S&P Global Developed Sc	-0,220615916
Gold/USD	0,045702274
FTSE EPRA Nareit Global	-0,029729135
Invesco Emerging Marke	-0,089714299
UK Pound Sterling/US Do	-0,053107603
US Dollar/Japanese Yen I	-0,025223774
Bitcoin/USD	0,074824985
Ethereum/USD	0,10013644
Litecoin/USD	0,052198763
US 10 Years Treasury Not	0,007879718
Own Portfolio	0,006519066
MSCI International Worl	0,026145052

Table 13: Sharpe ratio

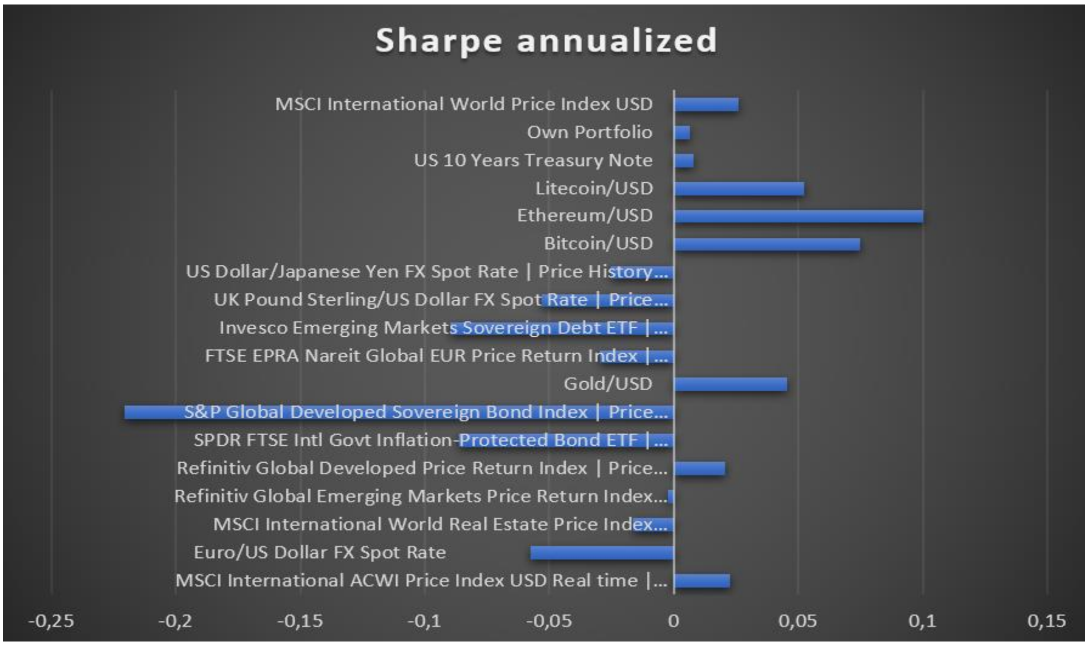


Figure 16: Sharpe ratio

Table 13 reveals that cryptocurrencies have the highest Sharpe ratios among all assets in our dataset, indicating they have delivered the highest return relative to their risk. Ethereum has the highest Sharpe ratio of 0.10, followed by Bitcoin (0.07482) and Litecoin (0.0521). Among non-crypto assets, Gold has the highest Sharpe ratio (0.045), followed by the MSCI international world price index (0.026). Comparing the Sharpe ratio of our constructed portfolio (0.0065) to that of the MSCI index (0.026), we find that the MSCI index outperforms our portfolio in terms of risk-adjusted returns. However, the lower Sharpe ratio of our own market portfolio designed to reflect the average crypto investor's investment opportunities suggests that an investor not able to invest in the MSCI index will yield an even better reward to risk ratio by investing in crypto compared to alternative investments available (own portfolio).

Based on our analysis, cryptocurrencies have demonstrated to be the best investment during the period of 2017-2022 based on their Sharpe ratios. However, when comparing the Sharpe ratios of our three cryptocurrencies with the findings of Parma-Wassvik (figure 17), we observe a decline in their Sharpe ratios. Ethereum's Sharpe ratio decreased from 1.98 to 0.1, Bitcoin's from 1.34 to 0.074, and Litecoin's from 0.746 to 0.052. This indicates that investors would have obtained lower returns relative to the associated risk of investing in cryptocurrencies during 2017-2022 compared to the period of 2010-2017.

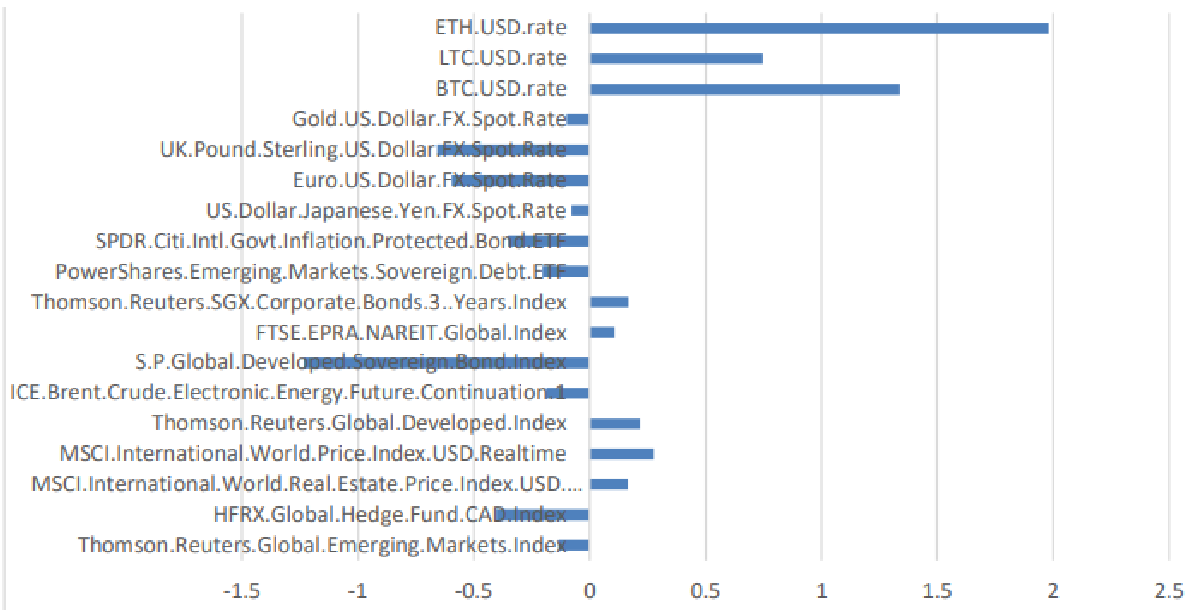


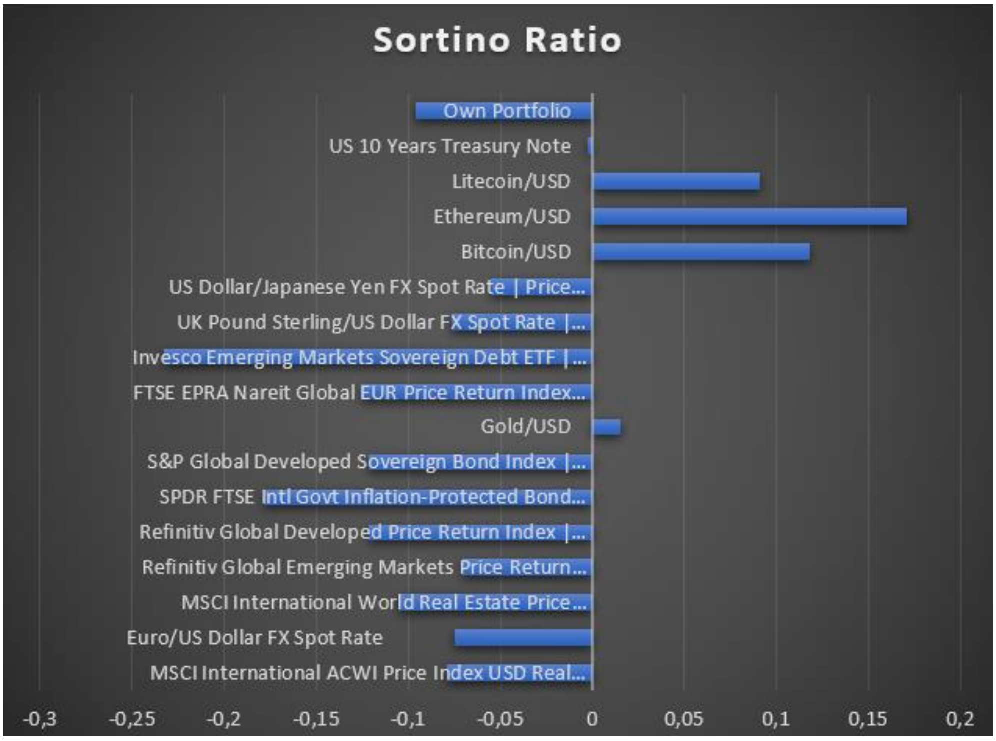
Figure 17: Sharpe ratio (Parma-Wassvik)

5.14 Sortino Ratio

Table 14 and figure 18 shows that out of all the assets in our dataset from 2017-2022, only four demonstrate a positive Sortino ratio. Ethereum had the highest value of 0.17, followed by Bitcoin with a value of 0.11, Litecoin with a value of 0.09, and gold, as the only non-cryptocurrency, with a Sortino ratio of 0.014. These findings indicate that these assets have proven to be good investments in our dataset during the period of 2017-2022, outperforming traditional assets.

Sortino Ratio	
ASSET	Values by using MSCI
MSCI International ACWI Price I	-0,078837391
Euro/US Dollar FX Spot Rate | P	-0,074595598
MSCI International World Real I	-0,104934652
Refinitiv Global Emerging Marke	-0,0704489
Refinitiv Global Developed Price	-0,121154454
SPDR FTSE Intl Govt Inflation-Pr	-0,178046382
S&P Global Developed Sovereig	-0,121424778
Gold/USD	0,014929621
FTSE EPRA Nareit Global EUR Pr	-0,125815559
Invesco Emerging Markets Sove	-0,233064442
UK Pound Sterling/US Dollar FX	-0,076734044
US Dollar/Japanese Yen FX Spot	-0,055452993
Bitcoin/USD	0,118156587
Ethereum/USD	0,171202273
Litecoin/USD	0,090771453
US 10 Years Treasury Note	-0,002829887
Own Portfolio	-0,096398165
MSCI International World Price	#DIV/0!

Table 14: Sortino ratio



When comparing the Sortino Ratio between the periods of 2017-2022 and 2010-2017 (figure 19), significant declines are observed. Ethereum's Sortino Ratio fell from 3.919 to 0.17, Bitcoin's declined from 2.144 to 0.11, and Litecoin experienced a decrease from 1.42 to 0.09. These decreases indicate that the risk-adjusted performance of these cryptocurrencies was lower in the period of 2017-2022 compared to 2010-2017

Figure 18: Sortino ratio

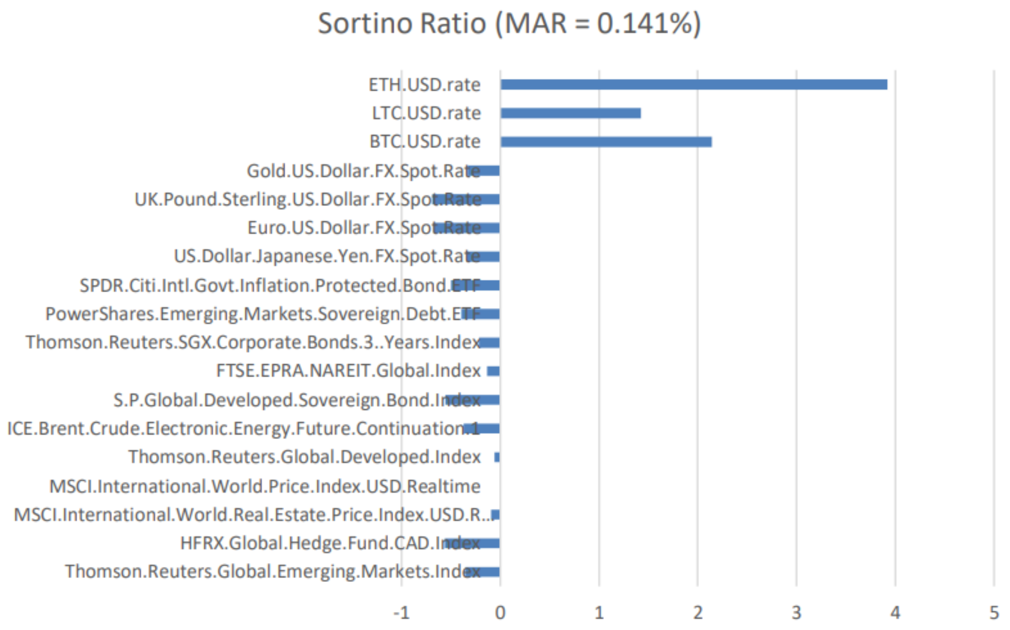


Figure 19: Sortino ratio (Parma-Wassvik)

despite the decrease in Sortino Ratio ratios for cryptocurrencies, our findings indicate that cryptocurrencies (and Gold/USD) have proven to be a favorable investment asset during the period of 2017-2022 compared to other assets in our dataset.

5.15 The efficient frontier and the equal and optimal weighted portfolio

In this section, we present our findings on efficient frontiers and optimal weighted portfolios using the three datasets described in chapter 4.3: our dataset from 2017-2022, Parma and Wassvik's dataset from 2010-2017 (including all assets but with only Bitcoin as cryptocurrencies), and Parma and Wassvik's dataset from 2015-2017 (including all assets and all cryptocurrencies).

For each dataset, we constructed efficient frontiers to analyze the risk-return relationship and determined the optimally weighted portfolios and if crypto should be included. Each dataset is presented separately, with an efficient frontier graph illustrating the assets involved, a table displaying the coordinates of the optimally weighted portfolios based on their risk and return characteristics (coordinates to the efficient frontier graph), and an additional table showcasing both equally and optimally weighted portfolios. Detailed calculations and the covariance-variance matrix can be found in the attached data for further details.

Table 15, 17, and 19 have been scaled to maximize space utilization for better readability. As a result, the table references are placed on the following page. For a clearer visualization, we recommend referring to the attached dataset.

5.15.1 The efficient frontier and optimal weighted portfolio with data from 2017-2022

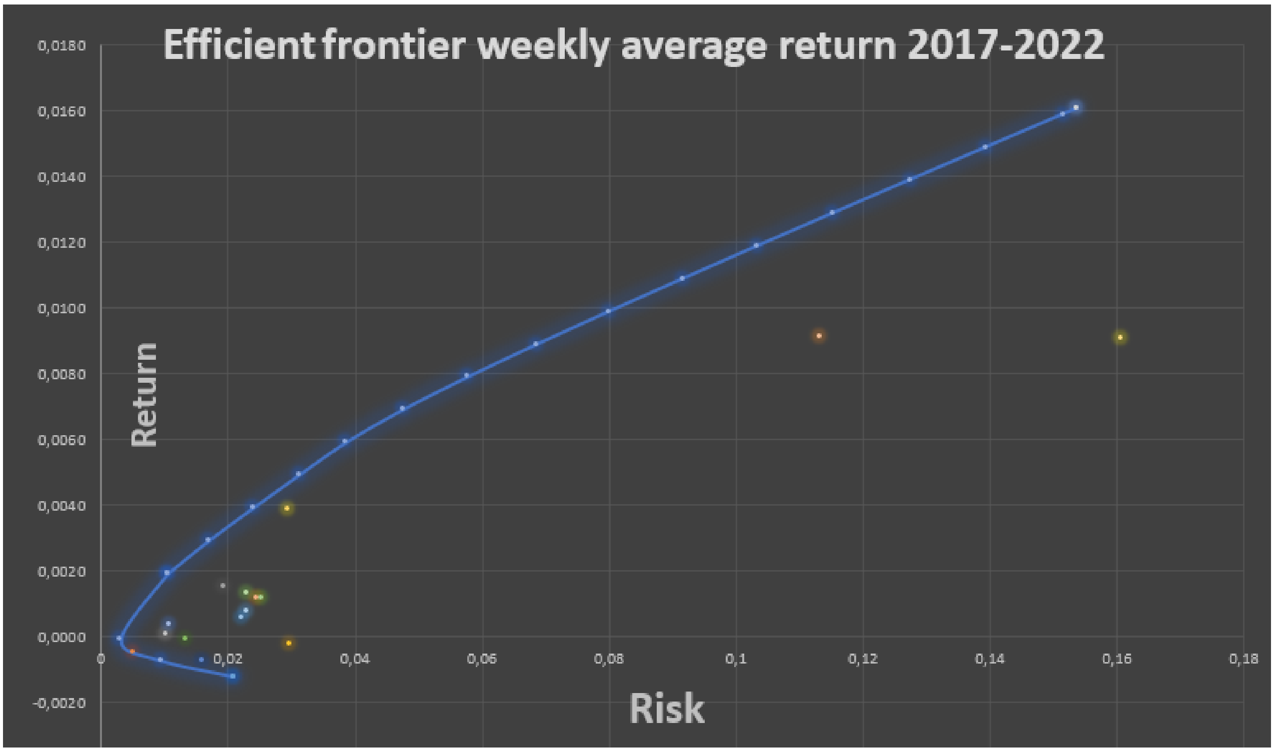


Figure 20: Efficient frontier 2017-2022

Expected weekl	-0,0012079	-0,0007195	-8,15919E-05	0,001918408	0,001918408	0,002918408	0,003918408	0,004918408	0,005918408	0,006918408	0,007918408	0,0089184	0,009918408	0,0109184	0,0119184	0,0129184	0,0139184	0,0149184	0,0159184	0,016101
Risk (variance)	0,000431566	8,65191E-05	9,37614E-06	0,000109395	0,000109117	0,000284829	0,000570607	0,000967988	0,001486033	0,002258608	0,003335069	0,004717	0,006404534	0,0083975	0,0106961	0,0133001	0,0162096	0,0194247	0,0229453	0,023621
STD	0,020774167	0,009301562	0,003062048	0,010459228	0,010445902	0,016876884	0,023887383	0,031112509	0,038549096	0,04752481	0,057750053	0,0686807	0,080028331	0,0916381	0,1034217	0,115326	0,1273171	0,1393725	0,151477	0,153691
Sharp ratio	-0,09000047	-0,14850031	-0,242771053	0,120144945	0,120298209	0,133710894	0,13633236	0,136813885	0,136361776	0,13164962	0,1256557	0,1202174	0,115666829	0,1119253	0,1088419	0,106278	0,1041229	0,1022915	0,1007191	0,1004559
MSCI Internatio	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Euro/US Dollar I	0	0	0,06593596	0,030552014	0,019211204	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSCI Internatio	0	0	0	0,232470582	0,224511274	0,394195996	0,565461775	0,737004449	0,82635414	0,753079796	0,671068112	0,5890564	0,507044751	0,4250331	0,3430214	0,2610097	0,178998	0,0969864	0,0149747	0
Refinitiv Global	0	0	0,025551501	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Refinitiv Global	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SPDR FTSE Inl	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S&P Global De	0	0,630112137	0,609543294	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gold/USD	0	0	0,040154584	0,190901767	0,216870971	0,157386745	0,088393954	0,021821822	0	0	0	0	0	0	0	0	0	0	0	0
FTSE EPRA Na	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Invesco Emergi	1	0,369887843	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UK Pound Sterl	0	0	0,001901733	0,000986944	0,000912844	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
US Dollar/Japar	0	0	0,256912928	0,51317426	0,506932744	0,387249841	0,248384731	0,111030446	0	0	0	0	0	0	0	0	0	0	0	0
Bitcoin/USD	0	0	0	4,12878E-05	4,15888E-05	4,367E-05	0,014153494	0,019279791	0,015349149	0	0	0	0	0	0	0	0	0	0	0
Ethereum/USD	0	0	0	0,03187317	0,0315194	0,061123777	0,083606089	0,110863529	0,158296754	0,246920204	0,328931887	0,4109436	0,492955248	0,5749669	0,6569786	0,7389903	0,821002	0,9030136	0,9850253	1
Litecoin/USD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Own Portfolio	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSCI Internatio	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 15: Efficient frontier portfolios 2017-2022

Figure 20 is a visualization of the efficient frontier for the 2017-2022 dataset. The efficient frontier is the optimal set of portfolios returning the highest return for a given risk or the lowest risk for an expected return (Ganti, 2022). Figure 20 gives a clear visualization that you can improve the return of the portfolio for the same amount of risk by diversifying into other assets. (Berk and DeMarzo, 2020. p412)

Table 15 shows the optimal return for a given risk used to graph the efficient frontier. Looking at table 15 and figure 20 we see that if we want the lowest weekly return with the lowest risk, we should invest all our money in Invesco Emerging Markets Sovereign Debt ETF giving us a weekly return of -0.0012 and a sharp ratio of -0.09. However, as we start to combine assets, we can optimize the Sharpe ratio. By Investing 50% in MSCI International World Real Estate Price Index, 8% in Gold, 20% in US/Yen, 1,4% in Bitcoin and 8,3% in Ethereum we will have similar risk but a weekly return of 0.0039. By investing 6.5% in Euro/USD, 2.5% in Refinitiv Global Emerging Markets Price Return Index, 60% in SPDR FTSE Intl Govt Inflation-Protected Bond, 4% in Gold, 0.19% in UK Pound Sterling/US Dollar and 25% in US Dollar/Japanese Yen we achieve the lowest risk possible with the highest return (min var portfolio). If an investor wants the highest return for the highest possible risk, he needs to invest 100% of his money in Ethereum giving an expected weekly return of 0.016, with a variance and standard deviation of 0.023 and 0.15 giving a Sharpe ratio of 0.1. Note that we did not include the risk-free rent as we only wanted to showcase the combination of our risky assets.

Optimal weighted Portfolio	Weights		
MSCI International ACWI Price Index USI	0	Expected weekly return	0,005285151
Euro/US Dollar FX Spot Rate | Price Histc	0	Risk (variance)	0,001141566
MSCI International World Real Estate Pr	0,799022975	STD	0,033787073
Refinitiv Global Emerging Markets Price	0	Sharp ratio	0,136838304
Refinitiv Global Developed Price Return I	0		
SPDR FTSE Intl Govt Inflation-Protected I	0		
S&P Global Developed Sovereign Bond Ir	0		
Gold/USD	0		
FTSE EPRA Nareit Global EUR Price Retu	0		
Invesco Emerging Markets Sovereign De	0		
UK Pound Sterling/US Dollar FX Spot Rat	0		
US Dollar/Japanese Yen FX Spot Rate | P	0,058970638		
Bitcoin/USD	0,021107607		
Ethereum/USD	0,12089878		
Litecoin/USD	0		
Own Portfolio	0		
MSCI International World Price Index US	0		
Equally weighted Portfolio	**Weights**		
MSCI International ACWI Price Index USI	0,058823529	Expected weekly retunr	0,002514654
Euro/US Dollar FX Spot Rate | Price Histc	0,058823529	Risk (variance)	0,000810152
MSCI International World Real Estate Pr	0,058823529	STD	0,028463166
Refinitiv Global Emerging Markets Price	0,058823529	Sharp ratio	0,065097082
Refinitiv Global Developed Price Return I	0,058823529		
SPDR FTSE Intl Govt Inflation-Protected I	0,058823529		
S&P Global Developed Sovereign Bond Ir	0,058823529		
Gold/USD	0,058823529		
FTSE EPRA Nareit Global EUR Price Retu	0,058823529		
Invesco Emerging Markets Sovereign De	0,058823529		
UK Pound Sterling/US Dollar FX Spot Rat	0,058823529		
US Dollar/Japanese Yen FX Spot Rate | P	0,058823529		
Bitcoin/USD	0,058823529		
Ethereum/USD	0,058823529		
Litecoin/USD	0,058823529		
Own Portfolio	0,058823529		
MSCI International World Price Index US	0,058823529		

Table 16: Optimal and equally weighted portfolio 2017-2022

From table 16 we can see that if an investor invests an equal amount of money in all assets (5.8%), the portfolio will yield a weekly return of 0.00251, with a variance and standard deviation of 0.000810, 0.028 and a sharp ratio of 0.06509. However, this is not the optimal combination of assets.

The optimal combination of assets in this data set to achieve the highest Sharpe ratio (return given risk) would be to invest 79.9% in MSCI International World Real Estate Price Index, 5.8% in US Dollar/Japanese Yen, 2.1% in Bitcoin and 12% in Ethereum. This combination gives a Sharp ratio of 0.13 with an expected weekly return of 0.0052 and variance and standard deviation of 0.0011 and 0.033. This shows that Bitcoin and Ethereum should be included in a diversified portfolio with data between 2017-2022.

5.15.2 The Efficient frontier and optimal weighted portfolio with data from Parma-Wassvik only including Bitcoin.

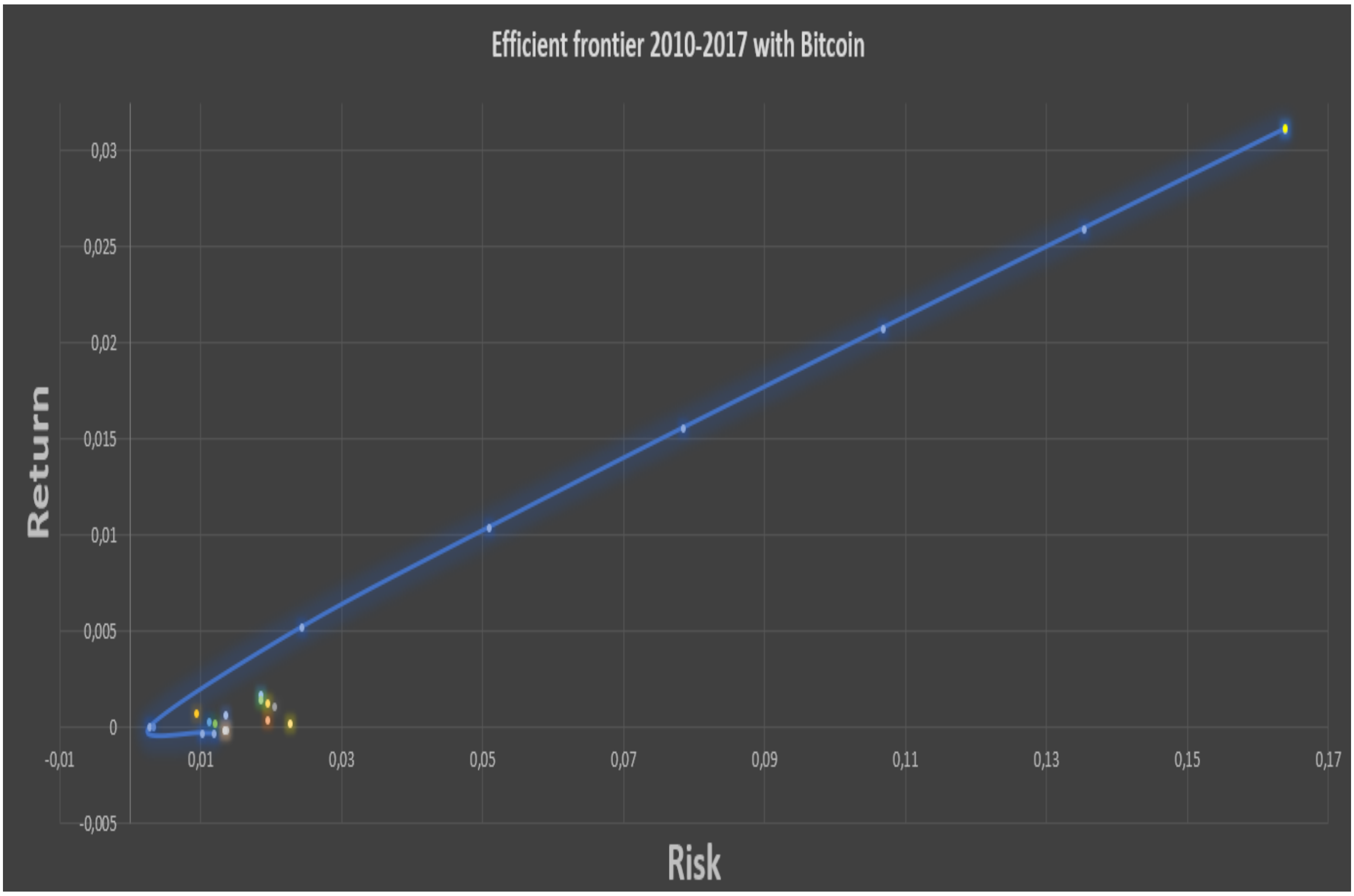


Figure 21: Efficient frontier 2010-2017 (Bitcoin)

Expected weekly retunr	-0,000331277	-0,000308799	2,24786E-05	0,005210943	0,010399408	0,015587872	0,020776336	0,025964801	0,031153265
risk (variance)	0,000139192	0,000102928	7,52021E-06	0,000591398	0,002587064	0,006155277	0,011387832	0,018285103	0,026847089
STD	0,011797961	0,010145353	0,0027423	0,024318681	0,050863188	0,078455576	0,106713788	0,13522242	0,163850813
sharp ratio	-0,084172339	-0,095667776	-0,233127691	0,187064351	0,191447355	0,190248903	0,188490654	0,187121455	0,186092947
Thomson Reuters Global Emerging Markets Index	0	0	0	0	0	0	0	0	0
HFRX Global Hedge Fund CAD Index	0	0,125992511	0,075314975	0	0	0	0	0	0
MSCI International World Real Estate Price Index USD Realtime	0	0	0	0	0	0	0	0	0
MSCI International World Price Index USD Realtime	0	0	0	0,361414091	0,677051205	0,528155736	0,352103817	0,176051904	0
Thomson Reuters Global Developed Index	0	0	0	0	0	0	0	0	0
ICE Brent Crude Electronic Energy Future Continuation 1	0	0,047820411	0,007034825	0	0	0	0	0	0
S&P Global Developed Sovereign Bond Index	0	0	0,774219106	0	0	0	0	0	0
FTSE EPRA/NAREIT Global Index	0	0	0	0	0	0	0	0	0
Thomson Reuters SGX Corporate Bonds 3+ Years Index	0	0	0	0,301467581	0	0	0	0	0
PowerShares Emerging Markets Sovereign Debt ETF	0	0	0	0	0	0	0	0	0
SPDR Citi Intl Govt Inflation-Protected Bond ETF	0	0	0	0	0	0	0	0	0
US Dollar/Japanese Yen FX Spot Rate	0	0	0,015177338	0,201080002	0,026243413	0	0	0	0
Euro/US Dollar FX Spot Rate	0	0	0,024230828	0	0	0	0	0	0
UK Pound Sterling/US Dollar FX Spot Rate	1	0,826187077	0,104022929	0	0	0	0	0	0
Gold/US Dollar FX Spot Rate	0	0	0	0	0	0	0	0	0
BTC/USD rate	0	0	0	0,136038324	0,296705367	0,471844247	0,647896165	0,823948083	1

Table 17: Efficient frontier portfolios 2010-2017 (Bitcoin)

The efficient frontier for the dataset from 2010-2017, depicted in Figure 21 and summarized in Table 17, focuses solely on Bitcoin. Ethereum and Litecoin were excluded from the analysis to minimize missing values, as the earliest observation of Ethereum was on 7.08.2015 and Litecoin on 25.10.2013. This allows us to isolate the impact of Bitcoin in constructing a portfolio based on this dataset.

As seen in table 17 and figure 21, an investor can get the lowest return given risk by investing 100% in UK Pound Sterling/US Dollar, this will yield a weekly average return of -0.003 and a variance and standard deviation of 0.001 and 0.011. The highest return given possible risk would be to invest 100% in Bitcoin while the minimum variance portfolio would be to invest 7% in HFRX Global Hedge Fund CAD, 0.7% in ICE Brent Crude Electronic Energy Future Continuation, 77% in S&P Global Developed Sovereign Bond Index, 10% in Pound/USD, 2.4% in Euro/Usd and US/yen giving a variance of 0.0000075.

Optimally- Weighted Portfolio	Weights		
Thomson Reuters Global Emerging Mar	0	Expected weekly retunr	0,010946107
HFRX Global Hedge Fund CAD Index	0	risk (variance)	0,002884912
MSCI International World Real Estate P	0	STD	0,053711374
MSCI International World Price Index L	0,685657391	sharp ratio	0,191473822
Thomson Reuters Global Developed Ind	0		
ICE Brent Crude Electronic Energy Futur	0		
S&P Global Developed Sovereign Bond I	0		
FTSE EPRA/NAREIT Global Index	0		
Thomson Reuters SGX Corporate Bonds	0		
PowerShares Emerging Markets Soverei	0		
SPDR Citi Intl Govt Inflation-Protected E	0		
US Dollar/Japanese Yen FX Spot Rate	0		
Euro/US Dollar FX Spot Rate	0		
UK Pound Sterling/US Dollar FX Spot Ra	0		
Gold/US Dollar FX Spot Rate	0		
BTC/USD rate	0,314342609		
Equally weighted portfolio	**Weights**		
Thomson Reuters Global Emerging Mar	0,0625	Expected weekly retunr	0,002402003
HFRX Global Hedge Fund CAD Index	0,0625	risk (variance)	0,000196655
MSCI International World Real Estate P	0,0625	STD	0,014023389
MSCI International World Price Index L	0,0625	sharp ratio	0,124094001
Thomson Reuters Global Developed Ind	0,0625		
ICE Brent Crude Electronic Energy Futur	0,0625		
S&P Global Developed Sovereign Bond I	0,0625		
FTSE EPRA/NAREIT Global Index	0,0625		
Thomson Reuters SGX Corporate Bonds	0,0625		
PowerShares Emerging Markets Soverei	0,0625		
SPDR Citi Intl Govt Inflation-Protected E	0,0625		
US Dollar/Japanese Yen FX Spot Rate	0,0625		
Euro/US Dollar FX Spot Rate	0,0625		
UK Pound Sterling/US Dollar FX Spot Ra	0,0625		
Gold/US Dollar FX Spot Rate	0,0625		
BTC/USD rate	0,0625		

Table 18: Optimal and equally weighted portfolios 2010-2017 (Bitcoin)

As seen from table 18, the optimal weighted portfolio for this dataset has 68,5% invested in MSCI International World Price Index and 31.4% in Bitcoin. This combination gives the highest Sharpe ratio of 0.19 with a variance and standard deviation of 0.00288 and 0.0537 giving a weekly average return of 0.0109. This finding shows that Bitcoin increases the Sharpe ratio and should be included in a portfolio based on this dataset as it improves it.

5.15.3 The Efficient frontier and optimal weighted portfolio with data (2015-2017) from Parma-Wassvik including all assets.

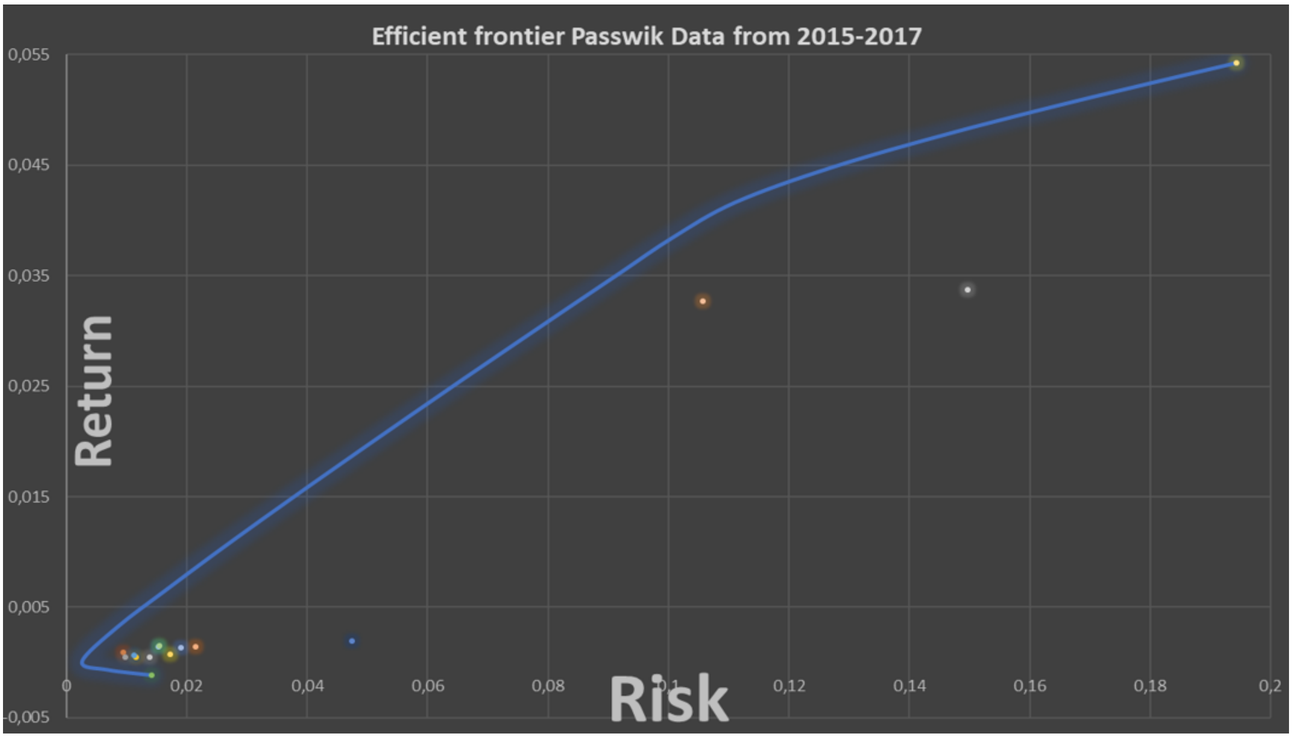


Figure 22: Efficient frontier 2015-2017 with all assets in Parma-Wassvik's dataset

Expected weekly returr	-0,0011856	-0,000697627	4,51234E-05	0,003245123	0,00644512	0,00964512	0,012845123	0,01604512	0,019245123	0,022445123	0,025645123	0,0288451	0,032045123	0,0352451	0,038445	0,041645	0,0448451	0,0480451	0,0512451	0,0542599
risk (variance)	0,0002016	4,75079E-05	6,77493E-06	7,40834E-05	0,00026598	0,00058451	0,001042793	0,00164485	0,002395848	0,003296305	0,004349394	0,0055603	0,006928984	0,0084556	0,01014	0,012351	0,0162286	0,0218538	0,0292272	0,0377732
STD	0,0141987	0,006892598	0,002602869	0,008607172	0,01630903	0,02417669	0,032292311	0,04055674	0,048947396	0,057413459	0,065949934	0,0745671	0,08324052	0,0919542	0,100698	0,111137	0,1273915	0,1478304	0,1709595	0,1943533
sharpe ratio	-0,130112	-0,197227723	-0,236916041	0,300137922	0,35460952	0,37157023	0,377282955	0,37930412	0,379659395	0,379411708	0,3788228	0,3779592	0,377019972	0,3760933	0,375216	0,368764	0,346831	0,3205249	0,295879	4,0026674
Thomson Reuters Global Emerging Markets Index	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HFRX Global Hedge Fund CAD Index	0	0	0,022745446	0,04118041	0,0481956	0,01254046	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSCI International World Real Estate Price Index USD Realtime	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSCI International World Price Index USD Realtime	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomson Reuters Global Developed Index	0	0	0,055522504	0,131758017	0,21826902	0,27176206	0,257829814	0,19360584	0,102770391	0,011934971	0	0	0	0	0	0	0	0	0	0
ICE Brent Crude Electronic Energy Future Continuation 1	0	0	0,002742161	0,006911755	0,00880411	0,0189392	0,028394041	0,04046109	0,054962113	0,069463034	0,061820443	0,0534027	0,043788181	0,0341737	0,024559	0	0	0	0	0
S&P Global Developed Sovereign Bond Index	0	0,32732754	0,690483416	0,437494618	0,15786807	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FTSE EPRA/NAREIT Global Index	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomson Reuters SGX Corporate Bonds 3+ Years Index	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PowerShares Emerging Markets Sovereign Debt ETF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SPDR Citi Intl Govt Inflation-Protected Bond ETF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
US Dollar/Japanese Yen FX Spot Rate	0	0,223789774	0,072932003	0,040475989	0,00633536	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Euro/US Dollar FX Spot Rate	0	0	0,111862013	0,184760177	0,20248073	0,16376458	0,045718747	0	0	0	0	0	0	0	0	0	0	0	0	0
UK Pound Sterling/US Dollar FX Spot Rate	1	0,448882686	0,043712457	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gold/US Dollar FX Spot Rate	0	0	0	0,086401028	0,21464077	0,31319539	0,366484725	0,38095841	0,373060181	0,365162	0,300860026	0,2255509	0,151392493	0,077234	0,003075	0	0	0	0	0
BTC/USD rate	0	0	0	0,040105737	0,0813203	0,12535503	0,172122947	0,22079351	0,27056129	0,320329221	0,370530349	0,4206435	0,470827939	0,5210125	0,571197	0,502485	0,3757272	0,2489692	0,1222114	0
LTC/USD rate	0	0	0	0,007942934	0,01729027	0,02682068	0,037571647	0,04714589	0,055353519	0,064761065	0,071967961	0,0789128	0,085866984	0,0928211	0,099775	0,086573	0,0638685	0,0411639	0,0184591	0
ETH/USD rate	0	0	0	0,022969333	0,04479576	0,06762259	0,091878063	0,11703525	0,142692489	0,168349693	0,194821208	0,22149	0,248124329	0,2747586	0,301393	0,410942	0,5604043	0,7098669	0,8593295	1

Table 19: Efficient frontier portfolios 2015-2017

Optimally weighted portfolio	Weights		
Thomson Reuters Global Emerging M	0	Expected weekly retunr	0,018978347
HFRX Global Hedge Fund CAD Index	0	risk (variance)	0,00232753
MSCI International World Real Estate	0	STD	0,048244484
MSCI International World Price Index	0	sharpe ratio	0,379661281
Thomson Reuters Global Developed I	0,108758823		
ICE Brent Crude Electronic Energy Futu	0,054770338		
S&P Global Developed Sovereign Bon	0		
FTSE EPRA/NAREIT Global Index	0		
Thomson Reuters SGX Corporate Bonc	0		
PowerShares Emerging Markets Sover	0		
SPDR Citi Intl Govt Inflation-Protected	0		
US Dollar/Japanese Yen FX Spot Rate	0		
Euro/US Dollar FX Spot Rate	0		
UK Pound Sterling/US Dollar FX Spot R	0		
Gold/US Dollar FX Spot Rate	0,374316108		
BTC/USD rate	0,266334767		
LTC/USD rate	0,055243957		
ETH/USD rate	0,140576007		
sum	1		
Equalyy weighted portfolio	**Weights**		
Thomson Reuters Global Emerging M	0,055555556	Expected weekly retunr	0,007266726
HFRX Global Hedge Fund CAD Index	0,055555556	risk (variance)	0,00041064
MSCI International World Real Estate	0,055555556	STD	0,020264262
MSCI International World Price Index	0,055555556	sharpe ratio	0,325940384
Thomson Reuters Global Developed I	0,055555556		
ICE Brent Crude Electronic Energy Futu	0,055555556		
S&P Global Developed Sovereign Bon	0,055555556		
FTSE EPRA/NAREIT Global Index	0,055555556		
Thomson Reuters SGX Corporate Bonc	0,055555556		
PowerShares Emerging Markets Sover	0,055555556		
SPDR Citi Intl Govt Inflation-Protected	0,055555556		
US Dollar/Japanese Yen FX Spot Rate	0,055555556		
Euro/US Dollar FX Spot Rate	0,055555556		
UK Pound Sterling/US Dollar FX Spot R	0,055555556		
Gold/US Dollar FX Spot Rate	0,055555556		
BTC/USD rate	0,055555556		
LTC/USD rate	0,055555556		
ETH/USD rate	0,055555556		

Table 20: Optimal and equally weighted portfolios 2015-2017

Figure 20 and table 19 illustrate the efficient frontier derived from the dataset of Parma and Wassvik, covering the period from 2015-2017 (Dataset 3), which includes all the assets. Table 20 presents the optimally weighted portfolio based on risk and return, indicating that the portfolio should include 37.4% Gold, 26.6% Bitcoin, 5.5% Litecoin, 14% Ethereum, 5% Ice Brent Crude, and 10.8% Thomson Reuters Global Developed Index. This gives the highest Sharpe ratio of 0.37, further highlighting the importance of including cryptocurrencies in a diversified portfolio.

To sum up our findings using the three different efficient frontiers, Cryptocurrencies has in all cases contributed to the portfolio performance and has in all cases been included in the optimally weighted portfolio, meaning the best overall portfolio possible includes cryptocurrencies given the dataset. This shows that crypto, more specifically Ethereum and bitcoin, should be included in a well-diversified portfolio given data from 2017-2022.

6 Conclusion:

In this study, we aimed to reevaluate the conclusion of Parma and Wassvik's thesis that examined the performance of cryptocurrencies as investments from 2010 to 2017. Our objective was to determine whether cryptocurrencies continue to be a lucrative investment opportunity in the subsequent period from 2017 to 2022 and if they should be included in a diversified portfolio, considering the significant volatility experienced by the crypto market in recent years. We also included our own constructed portfolio for reflecting the average crypto investors benchmark as not all crypto investors have access to MSCI International World Price Index.

Upon analyzing the data, we find that the initial thesis's conclusion remains valid. While cryptocurrencies have indeed demonstrated the potential for higher returns compared to traditional assets, we observed that their performance has diminished during the 2017-2022 period.

Our research indicates that although cryptocurrencies, namely Ethereum and Bitcoin, continue to outperform all traditional assets in our data set, their overall return has been less remarkable in recent years. Even though the variance has decreased for all the cryptocurrencies indicating less volatility than in 2010-2017, the bigger decrease in return has made crypto perform worse considering the risk. The decrease in risk and return compared to (Parma-Wassvik) can be explained by the high and constant weekly price growth crypto currencies experienced from 2010 to 2017 giving high variance (because of the rapid and high growth) and high average return, while crypto in 2017 to 2022 have experienced both negative and positive price changes and less extreme observation around the mean giving a lower return and lower variance.

When considering the risk-return tradeoff, cryptocurrencies still offer potential benefits, but their performance metrics do not surpass those of the previous period. It is worth noting that data used in Parma-Wassvik are affected by extreme positive observations (outliers) as in 2017 due to the rapid increase in crypto prices during this period. These extreme observations might have given a "misleading" variance that has also given misleading metrics. In our study, we capture a dramatic price increase but also a dramatic price decrease, giving us less outliers and therefore more reliable data with more reliable metrics that concludes cryptocurrencies outperform all assets despite their variance.

In conclusion, while the original thesis concluded that cryptocurrencies have been an attractive investment opportunity and should be included in a well-diversified portfolio, our study with new and more reliable data confirms **that cryptocurrencies should be included in a well-diversified portfolio and have shown to be a superior investment compared to alternative assets available in our dataset.**

It is important to emphasize that our study focused on the period from 2017 to 2022, and future research should continue to monitor the performance of cryptocurrencies to provide a more comprehensive understanding of their long-term investment potential.

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8 Attachments

Attachment 1