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HEC MONTRÉAL

The Diversification Benefits of Cryptocurrencies in Asset Allocation for a US Investor

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Résumé

Cette analyse se concentre sur les avantages de diversification du bitcoin et d'autres crypto-monnaies dans un portefeuille par ailleurs bien diversifié. Dans cette thèse, je sélectionne 15 monnaies virtuelles représentatives et je construis un portefeuille de référence composé d'FNBs représentatifs qui suivent différentes classes d'actifs. Sur la base de la théorie du portefeuille de Markowitz, je réalise une analyse de portefeuille d'investissement sur les 15 monnaies virtuelles sélectionnées en utilisant la méthode moyenne-variance. Le portefeuille optimal avec le ratio de Sharpe maximum est obtenu empiriquement, les rendements mensuels du portefeuille hors échantillon sont calculés en utilisant l'approche de la fenêtre glissante, et les performances des portefeuilles résultants sont comparées. Les résultats montrent que si les crypto monnaies sont caractérisées par un risque élevé et que la pondération optimale de leur portefeuille est relativement faible, elles contribuent également à des rendements plus élevés et peuvent donc être considérées comme un actif de portefeuille diversifié.

Mots clés : crypto monnaies, Optimisation de portefeuille, Approche moyenne-variance, Hors échantillon

Méthodes de recherche : Optimisation de la moyenne-variance, approche de la fenêtre mobile

Abstract

This analysis focuses on the diversification benefits of Bitcoin and other cryptocurrencies in an otherwise well-diversified portfolio. In this thesis, I select 15 representative virtual currencies and I construct a benchmark portfolio consisting of representative ETFs tracking different asset classes. On the basis of Markowitz's portfolio theory, I conduct a portfolio investment analysis on the 15 selected virtual currencies using the mean-variance method. The optimal portfolio with the maximum Sharpe ratio is obtained empirically, the out-of-sample portfolio monthly returns are calculated using the rolling window approach, and the performance of the resulting portfolios are compared. The results show that while cryptocurrencies are characterized by high risk and their optimal portfolio weights are relatively low, they also contribute to higher returns and can therefore be considered as a diversified portfolio asset.

Keywords: Cryptocurrency, Portfolio Optimization, Mean-Variance Approach, Out-of-Sample

Research methods: Mean-Variance Optimization, Rolling Window Approach

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List of abbreviations and acronyms

MVO	Mean-Variance Optimization
BTC	Bitcoin
ETH	Ethereum
DOGE	Dogecoin
LTC	Litecoin
XLM	Stellar
ETC	Ethereum-Classic
XMR	Monero
NEO	Neo
ZEC	Zcash
WAVES	Waves
DASH	Dash
XEM	Nem
DCR	Decred
SYS	Syscoin
SC	Siacoin
SHV	iShares Short Treasury Bond ETF
AGG	iShares Core U.S. Aggregate Bond ETF
GLD	SPDR Gold Shares
SPY	SPDR S&P 500 ETF Trust
IJH	iShares Core S&P Mid-Cap ETF
IJR	iShares Core S&P Small-Cap ETF
PDBC	Invesco Optimum Yield Diversified Commodity Strategy No K-1 ETF
VCIT	Vanguard Intermediate-Term Corporate Bond ETF
SHY	iShares 1-3 Year Treasury Bond ETF
BTC portfolio	benchmark portfolio with Bitcoin

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Chapter 1
Introduction

Over the past decade or so, various types of cryptocurrencies, such as Bitcoin, have become increasingly important in the financial markets. As more types of virtual currencies have appeared on the market, they have been increasingly investigated as a new type of financial asset, and their characteristics and role in asset portfolios have been brought to the attention of more investors. Increasingly, cryptocurrencies have begun to attract the interest of academics who wish to evaluate virtual currencies as an asset for inclusion in portfolios. Additionally, investors and portfolio managers have searched for new assets with hedging and safe-haven characteristics, and cryptocurrencies have been launched to the market as a result of the COVID-19 pandemic's terrible effects on both human health and the world's financial markets.

The analysis in this paper focuses on the impact of adding cryptocurrencies such as Bitcoin to an already diversified portfolio respectively, or more precisely, the impact that cryptocurrencies may have on the returns and risk of such a portfolio. This performance is compared to a benchmark portfolio without the virtual currency. I then repeat this process, comparing the performance of different virtual currencies. Finally, I conduct an analysis of portfolios formed of multiple virtual currencies to see if they have an impact on the investment performance. As the research data covers the global pandemic, the results are divided on a yearly basis for this study.

Mariana et al. (2021) shows that during the COVID-19 pandemic, BTC and ETH exhibited the risk aversion properties of the S&P 500 index. I explore whether 15 virtual currencies, including BTC and ETH, have diversified benefits by refining the performance measures of out-of-sample portfolio returns and by further exploring the reconstitution of virtual currencies. In addition, instead of selecting a single point in time for portfolio optimization, I adopt a rolling window approach, tracking and evaluating the performance of the out-of-sample monthly portfolios over an investment horizon of more than six years, while re-optimizing the portfolio weights each time the evaluation window is advanced forward.

I construct a benchmark portfolio by selecting basic asset classes, and on this basis, I first optimize the portfolio weights by adding a single type of virtual currency, such as Bitcoin, separately. The optimal weights of the new portfolio with the addition of a virtual currency (e.g., Bitcoin) are calculated using a rolling panel with an estimation window of 24 months and a 1-month progression to maximize the Sharpe ratio. The resulting covariance, portfolio returns, performance measures, and descriptive statistics results can be used to see if cryptocurrencies have a significant impact on the portfolio.

Secondly, to better identify the role of virtual currencies in a portfolio, I replace the historical virtual currency return data with different levels of expected returns for investors (e.g., 5%, 10%, 20%) and explores how different expected return levels for virtual currencies change the results.

I present the results on a yearly basis based on the steps described above to confirm in more details and accuracy whether the results derived from the selected data are influenced by historical events, such as the global pandemic that started in 2019.

Furthermore, I explore two other ways of constructing asset portfolios: one is to combine the selected 15 virtual currencies into a completely new asset class using equal weights and add this equally weighted new asset to the benchmark portfolio to try to calculate and analyze it; the other is to consider the dataset consisting of the 15 virtual currencies as a portfolio and to directly optimize this all-virtual currency portfolio.

This study contributes to the growing area of research on the investment portfolios of cryptocurrencies by exploring the role and influence of cryptocurrencies as an asset class in investment portfolios.

The results of this paper show that cryptocurrencies have a relatively low weighting in the optimal portfolio and thus the optimization of the benchmark portfolio differs little between different types of virtual currencies and is influenced by the global pandemic. The portfolios in which Bitcoin (BTC) and Litecoin (LTC) are located perform better, and the two portfolios after further processing also improve their performance relative to the benchmark portfolio. While cryptocurrencies have a high-risk characteristic, they also help to increase returns and can therefore be considered a diversified portfolio asset.

However, as 15 virtual currencies were selected for the study in this paper, the data is limited to the period going from October 2016 to March 2022. The relatively short time period of the study and the single analysis method used may make the data results less accurate. The time frame of the data could be extended in future studies, multiple models could be selected for separate analysis and comparison, and benchmark portfolios of investors from different countries, different investment sectors and different risk appetites could be constructed for analysis and comparison to draw more conclusions.

The overall structure of the study takes the form of 7 chapters, including this introductory chapter and the Literature Review Chapter that follows.

Chapter three begins by laying out the methodology used for this study. The fourth chapter is concerned with the data selection and the descriptive statistic results for the benchmark portfolio and cryptocurrencies. The fifth chapter describes the processing of the data, the results of the out-of-sample tests, and the performance measures of the different crypto portfolio returns. Chapter six contains further analysis, including splitting the data on yearly basis, regarding the cryptocurrency dataset as the portfolio and doing the optimization, and adding average-weighted cryptocurrencies as a new asset class into the benchmark portfolio. The final chapter concludes.

Chapter 2
Literature review

Bitcoin is a virtual currency derived from mathematical cryptography, which was originally conceived as an alternative to government-backed currencies. It is a cryptocurrency based on decentralization, using a peer-to-peer network with consensus initiative, open source, and using blockchain as the underlying technology (Nakamoto, 2008). Bitcoin's founders argued that fiat currencies do not work well as a store of value or medium of exchange due to excessive inflation and high transaction costs. However, the financial characteristics of Bitcoin (e.g. volatility) have changed significantly since its trading price 'crashed' in 2013, when some of the early properties that made it a safe haven completely disappeared (Kristoufek, 2015). In 2018, the price of Bitcoin fell by around 60% from the peak reached in 2017, and it is now seen more as a speculative asset than a payment instrument (Horra, Fuente and Perote, 2019).

Numerous additional cryptocurrencies entered the market after BTC's launch. The legality of BTC and ETH as investment vehicles was further enhanced by the Chicago Mercantile Exchange, which introduced a futures contract with BTC as the underlying asset in December 2017 and a futures contract with ETH as the underlying asset in February 2021(Corbet et al., 2018). Such developments have led to more virtual currencies gradually appearing on the market and attention being paid to the role and value of virtual currencies in the investment space.

Many researchers classify virtual currencies as assets rather than currencies, others consider them to be commodities, while others simply identify Bitcoin as a new type of hybrid asset. Grinberg (2011) questions the classification of Bitcoin as a security, investment contract, commodity, or currency, arguing that Bitcoin's path to legitimacy will not be a smooth one, which will result in a volatile price. The difficulty of categorization due to the distinctive nature of digital currencies instead makes them well suited to the role of alternative assets in asset allocation, in line with the principle of diversification.

Many scholars have studied the behavior of bitcoin and cryptocurrency prices: Bariviera, Basgall, Hasperué and Naiouf (2017) argue that cryptocurrencies have high volatility and remote memory; Chaim and Laurini (2019) find a long-term memory dependence in cryptocurrency's returns. Compared to other assets, bitcoin returns are more volatile than gold and exchange rates (Dwyer, 2015), and its market is less efficient than gold, stock and currency markets (Al-Yahyaee, Mensi, and Yoon, 2018). The hedging and diversification characteristics of virtual currencies have also been studied, with Akyildirim, Corbet, Lucey, Sensoy, and Yarovaya (2020) arguing that there is a correlation between bitcoin and market stress. Studying the risk and volatility of digital currencies is significant as they have the potential to be an excellent and essential portfolio for asset allocation.

Since the seminal work of Markowitz (1952) and Markowitz (1976), the financial sector has stressed the value of portfolio diversification, and numerous studies have looked at the ideal asset mix that maximizes returns by minimizing risk (i.e., volatility).

There have been increasing attempts to explore whether virtual currencies can be used not only as a payment instrument but also as a financial asset. Dyhrberg (2016) argues that bitcoin has a role in the financial system and in investment asset portfolios. Similar to this viewpoint, Katsiampa (2017) asserts that studying bitcoin's volatility is important because of the rapid growth of bitcoin's market capitalization and its increasing prominence in financial markets.

In a diversified portfolio, integrating bitcoin can help to lower risk and is a good diversifier for equity portfolios, according to Guesmi, Saadi, Abid, and Ftiti (2019). Kajtazi and Moro (2019) also found that bitcoin can help to enhance portfolio performance. Baumöhl (2019) found that cryptocurrencies have relatively low correlations with other assets, which may indicate that Bitcoin is an asset that helps diversify a portfolio. Symitsi and Chalvatzis (2019)'s study suggests that bitcoin has higher diversification benefits than commodities. However, others argue that due to its extreme volatility, poor liquidity, and expensive transactions, bitcoin is not a secure investment (Smales, 2019).

According to Eisl et al. (2015), the introduction of bitcoin to a portfolio of US assets that is already well-diversified raises both the portfolio's expected return and risk. They recommend allocating bitcoin to such portfolios to maximize the Sharpe ratio. Brière et al. (2015) also demonstrate that the Sharpe ratio increases when bitcoin is included in a portfolio of US assets that is already well-diversified. Similar results were obtained by adding virtual currencies to portfolios of foreign currencies, commodities, equities, and ETFs (Adrianto & Diputra, 2017).

However, due to the relatively short period of time since the creation of virtual currencies, research on the diversification benefits of virtual currencies is not considered comprehensive, with few studies comparing the role of different virtual currencies in a portfolio in detail and fewer studies with sample data years covering the global pandemic. Therefore, in order to examine the diversification returns of Bitcoin and other digital currencies in more depth, I constructed benchmarks portfolios based on US asset classes proxied by ETF funds, using the methodology of Eisl et al. (2015) and others as a reference, and analyses the expected returns and risks of different virtual currencies when added to a plus-quota portfolio to see whether the allocation of virtual currencies in such portfolios can maximize the Sharpe ratio.

Chapter 3
Methodology

The methodological approach taken in this study is based on mean-variance optimization using a rolling window approach. By employing a quantitative research approach, I attempt to illuminate the role of cryptocurrencies in portfolio management for investors and find out the optimal combination of them.

A portfolio is a collection of stocks, bonds, and other financial assets. held by an investor for the purpose of diversifying risk. A portfolio of numerous securities lowers idiosyncratic risk while having a return that is a weighted average of the returns of those securities. However, the risk of the portfolio is not a weighted average of the hazards of those securities. Making investment decision is making a tradeoff between expected returns and risk and striving to achieve higher returns while minimizing portfolio risk.

3.1 Markowitz's Portfolio Theory

In his seminal paper, Markowitz (1952) used probability theory and quadratic programming to solve portfolio selection problems, which marked the birth of modern portfolio management theory.

The mean-variance model and the efficient frontier theory are both parts of Markowitz's portfolio theory, which is predicated on the notion that investors are risk averse and want to maximise expected returns. According to the theory, a portfolio's expected return and investment risk can be quantified in terms of mean and variance, respectively, and the goal of investment decisions is to identify the portfolio with the lowest investment risk for a given level of expected return or the highest expected return for a given level of risk. On the mean-variance coordinate system, the boundary of the portfolio area formed by multiple risky assets is a rightward-opening, up-and-down symmetric hyperbola, the upper half of which is called the "efficient frontier" of the portfolio. As the portfolio on the efficient frontier has the highest expected return for a given level of volatility, the asset allocation is only efficient if the portfolio is on the efficient frontier, where the portfolio can be optimally chosen according to the investor's specific preferences.

3.2.1 Markowitz's Portfolio Theory

The portfolio expected return is a weighted average of the expected returns of assets that make up the portfolio. The proportion of each asset invested in the portfolio is used as the weight.

The weight vector for a portfolio of n assets in period t is:

$$\omega_t = (\omega_1, \omega_2, \dots, \omega_n)^T$$

where ω_i is the proportion of the current value of asset i in the portfolio related to the portfolio value, and:

$$\omega_1 + \omega_2 + \cdots + \omega_n = 1$$

Assume that an investor invests in a portfolio consisting of n risky assets in a single investment period and r_i denotes the expected rate of return on the ith asset, the expected portfolio return is:

$$E(r_p) = \sum_{i=1}^{n} \omega_i E(r_i)$$

3.2.2 Portfolio Risk Measurement

Risk is represented by the variance or standard deviation of returns. The variance of a portfolio is a function of the variance of each asset and the covariance between assets. The relationship between asset returns can be expressed as a correlation coefficient or covariance.

If $V_{ij} = Cov[r_i, r_j]$ is the covariance between two assets r_i and r_j then the covariance matrix of all assets can be written as:

$$V = \begin{vmatrix} Var(r_1) & Cov(r_1, r_2) & \dots & Cov(r_1, r_n) \\ Cov(r_2, r_1) & Var(r_2) & \dots & Cov(r_2, r_n) \\ \dots & \dots & \dots & \dots \\ Cov(r_n, r_1) & Cov(r_n, r_2) & \dots & Var(r_n) \end{vmatrix}$$

$$= \begin{vmatrix} {\sigma_1}^2 & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & {\sigma_2}^2 & \dots & \sigma_{2n} \\ \dots & \dots & \dots & \dots \\ \sigma_{n1} & \sigma_{n2} & \dots & {\sigma_n}^2 \end{vmatrix}$$

Then the standard deviation of the portfolio should satisfy the following equation:

$$\sigma_p^2 = E\left[\left(\sum_{i=1}^{n} \omega_i r_i - \sum_{i=1}^{n} \omega_i E[r_i]\right)^2\right]$$

$$= \sum_{i,j=1}^{n} \omega_i \omega_j E\left[\,(r_i - E[r_i])\left(r_j - E[r_j]\right)\right] = \sum_{i,j=1}^{n} V_{i,j}\omega_i\omega_j$$

We can rewrite the equation in the form of a quadratic function:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} \omega_i\omega_j\rho_{ij}\sigma_i\sigma_j = \sum_{i=1}^{n}\sum_{j=1}^{n} \omega_i\omega_j Cov\left(r_i, r_j\right)$$

According to the above formula, the risk of a portfolio depends mainly on the weight and standard deviation of each asset, as well as the correlation coefficient between different assets. Therefore, investors should give preference to assets with low variance and low correlation coefficients between them in order to reduce investment risk. In practice, the sample mean and sample variance of historical return data are often used to estimate expected returns and risks.

3.2 Mean-Variance Optimization

According to Markowitz's logic, asset allocation is the distribution of different assets in a portfolio in order to achieve the best combination of investment risk and expected return, and portfolio theory uses the mean-variance model to balance these two key factors for investors. The mean is a weighted average of the expected returns of individual securities, weighted by the corresponding share of the investment, and represents the expected return of a portfolio. The variance is the return variance for the portfolio. Volatility, often known as the standard deviation of returns, is a measure of how risky a portfolio is.

3.3.1 Minimum Variance Optimization

Use the following matrix to represent:

$$\omega_t = (\omega_1, \omega_2, \dots, \omega_n)^T, e = (1,1, \dots, 1)^T;$$

$$\mu = (\mu_1, \mu_2, \dots, \mu_n)^T, \mu_i = E(r_i), i = 1, 2, \dots, n;$$

$$V = (V_{ij})_{i,j=1,2,\dots,n} = \left(Cov[r_i, r_j]\right)_{i,j=1,2,\dots,n}$$

Calling p a portfolio, $\mu_p = \omega^T \mu$ a portfolio return and $\sigma_p = (\omega^T V \omega)^{1/2}$ a portfolio risk, the selection problem for a mean-variance portfolio can be expressed as:

$$\begin{cases} \mathbf{min} \;\; \sigma_p^2 = \omega^T V \omega = \sum_{i,j=1}^{n} V_{i,j} \omega_i \omega_j \\ \boldsymbol{s.t} \;\; \omega^T e = \omega_1 + \omega_2 + \dots + \omega_n = 1 \\ \mu_p = \omega^T \mu = \omega_1 \mu_1 + \omega_2 \mu_2 + \dots + \omega_n \mu_n = \bar{\mu} \end{cases}$$

The solution $\bar{\omega}$ to this problem is known as the very small risk portfolio corresponding to the return $\bar{\mu}$.

3.3.2 Maximum Sharpe Ratio

Rational investors generally fix the risk they can take and seek the maximum return; or in fixing the expected return, chase away the minimum risk. The minimum variance optimization described above, while able to control risk by reducing the volatility of returns, does not lead to substantial expected returns. There is an alternative way of calculating risk (variance) and return in the mean-variance model, which is an alternative optimization strategy that seeks to minimize risk and maximize return - the maximum Sharpe ratio.

Introduced in 1966 by Nobel Laureate William Sharpe (1963), the Sharpe Ratio is used as a risk-adjusted measure of fund performance to help investors compare the return and risk of their investments. The Sharpe Ratio, therefore, calculates the excess return generated per unit of total risk taken. The Sharpe Ratio is the ratio of the excess expected return of a portfolio to its overall standard deviation, and is calculated as:

$$S_p = \frac{E[r_p] - R_f}{\sigma_p}$$

Where S_p denotes the Sharpe ratio, σ_p is the overall portfolio standard deviation, and R_f is the risk-free rate. The numerator calculates the spread and says that the excess return is obtained by comparing a particular investment with a benchmark representing the entire investment class. The standard deviation in the denominator shows the return's volatility, which corresponds to risk; a higher standard deviation denotes a higher risk. The higher the Sharpe ratio, the higher the return per unit of risk that the fund can achieve.

In short, the Sharpe ratio measures the excess return per unit of risk. The higher the ratio, the higher the excess return per unit of risk taken by the strategy.

Therefore, compared to minimum variance optimization, the maximum Sharpe ratio can be expressed as:

$$\begin{cases} \mathbf{max} \quad \mathrm{S_p} = \dfrac{E[r_p] - R_f}{\sigma_p} = \dfrac{E[r_p] - R_f}{\sqrt{\omega^T V \omega}} = \dfrac{\sum_{i=1}^{n} \omega_i E(r_i) - R_f}{\sqrt{\sum_{i,j=1}^{n} V_{i,j} \omega_i \omega_j}} \\ \boldsymbol{s.t} \quad \sum_{i=1}^{n} \omega_i = 1; \quad 0 \leq \omega_i \leq 1, \quad i = 1,2,\dots,n \end{cases}$$

Since the tangent line from the risk-free rate to the efficient frontier taps the frontier at these portfolios, portfolios that maximize Sharpe are also known as tangency portfolios.

In this study, the restriction $\omega_i > 0$ means that the risky asset is not shortable, so the ratio will not be negative.

3.3 Rolling Window Approach

A problem with point-in-time data is that it can be volatile and the data at a given time-point does not always represent characteristics well. Therefore, I use a rolling window: In order to improve the accuracy and reliability of the data analysis, historical data is collected according to a time period. This interval, which is the estimate window, is used to perform the calculations. When a time-series model is analyzed using a rolling-window approach, its stability over time can be assessed.

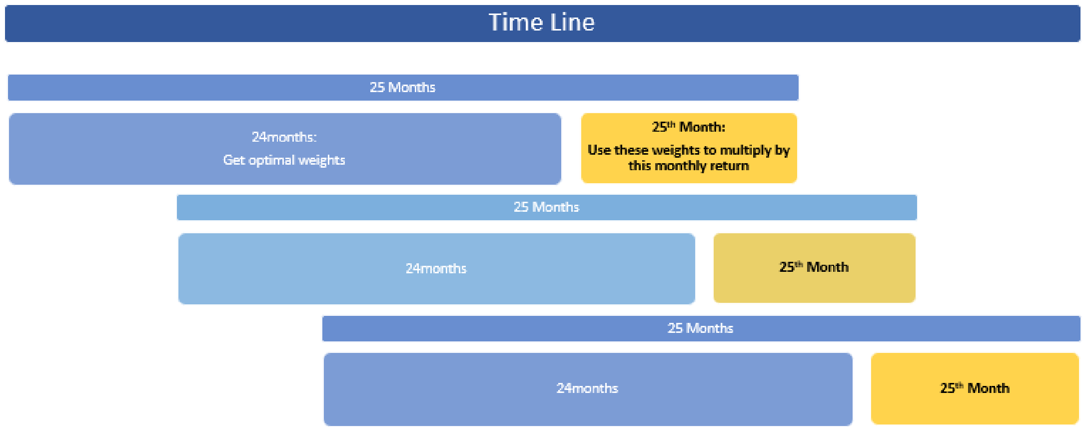

Figure 1 Rolling Window Approach

Notes: This figure shows the process of the implementation of the rolling window approach. The first three estimation windows are taken as examples.

For a dataset of length n, an estimation window of samples of length w is used for rolling estimations, moving forward 1 unit at a time until the end of the estimation window reaches the end of the dataset. That is, the first estimation window is [0, w] from the moment t = 0. The first month of data at the beginning of the estimation window is discarded when the rollover is performed and one month of data is added at the end. The second window is then [1, w+1] and the last window is [n - w, n], giving a final total of (n - w+1) windows. Figure 1 depicts this process graphically.

3.4 Portfolio Performance

Maximum Drawdown (MMD) is the maximum value of the drawdown of a product's net worth to its lowest point at any point in history during the selected period. This is done by measuring the drawdown rate of each net value and finding the largest one. For hedge funds and trading using quantitative strategies, MMD is a more significant risk indicator than volatility.

The formula can be expressed as follows：

$$drawdown = max \ \frac{P_i - P_j}{P_i}$$

Suppose *P* represents the net value of a day, *i* represents a day, *j* represents a day after i. P_i is the net value of the product on day i, and P_j is the net value of a day after P_i.

Chapter 4
Data Selection and Descriptive Statistic Results

Fifteen cryptocurrencies were selected for this study based on market capitalization and time horizon. nine main asset classes from different sectors were also selected to construct a benchmark portfolio, which can be used to conduct research on the diversification benefits of cryptocurrencies. In this chapter, in addition to the selection and pre-processing of the data, descriptive statistical results and correlation results are also presented for these processed datasets.

4.1 Data Selection

4.1.1 Select 15 Cryptocurrencies

The sample consists of monthly closing prices for fifteen cryptocurrencies retrieved from Coinmarketcap.com. I collected those cryptocurrencies which begin trading no later than **29-Oct-2016** and whose market capitalization is larger than 1 billion. This selection ensures that the time horizon of the data is greater than 5 years (during the period of 29/10/2016 to 30/06/2022). Therefore, the portfolios have a sufficient number of observations to provide meaningful inferences.

Table. 1 15 Cryptocurrencies

Name	Mnemonic	Start Year
Bitcoin	BTC	2010
Ethereum	ETH	2015
Dogecoin	DOGE	2013
Litecoin	LTC	2013
Stellar	XLM	2014
Ethereum-Classic	ETC	2016

Monero	XMR	2014
Neo	NEO	2016
Zcash	ZEC	2016
Waves	WAVES	2016
Dash	DASH	2014
Nem	XEM	2015
Decred	DCR	2016
Syscoin	SYS	2014
Siacoin	SC	2015

Notes: This table shows 15 cryptocurrencies which started trading no later than October 2016 and have more than 1 billion in market capitalization.

Monthly Returns are calculated by first taking the percentage change of two consecutive months' closing price, and then minus one. The formula is:

$$Monthly\ Returns = \frac{Closing\ Price\ on\ Last\ Day\ of\ Month}{Closing\ Price\ on\ Last\ Day\ of\ Previous\ Month} - 1$$

4.1.2 Main Asset Classes of Benchmark Portfolios

In order to achieve a well-diversified portfolio, I assume the position of a US investor and constructs a diversified portfolio of representative ETFs across a variety of asset classes including money market, gold, and fixed income. All asset classes are quoted in USD and data is collected via the ETF Database and the CRSP dataset. The total returns are calculated from the monthly adjusted close price of the ETFs, which is adjusted for splits and dividends.

$$ETF\ Returns_t = \frac{Adjusted\ close\ Price_t}{Adjusted\ close\ Price_{\ t-1}} - 1$$

The benchmark portfolio is constructed based on US asset classes proxied by ETF funds, which consists of different investable asset classes: one kind of Cryptocurrency combined with a Money Market ETF, Fixed-income ETF, Gold ETF, Large/Mid/Small cap Equity, Commodities ETF, Corporate Bonds ETF, and Treasury ETF. I choose the largest ETF in the list of ETF Database Categories from ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS). The nine ETFs are selected and shown in Table 2 below.

Table. 2 United States Main Asset classes

Name	**Mnemonic**	**Asset class**
iShares Short Treasury Bond ETF	SHV	Money Market ETF
iShares Core U.S. Aggregate Bond ETF	AGG	Fixed-income ETF
SPDR Gold Shares	GLD	Gold ETF
SPDR S&P 500 ETF Trust	SPY	Equity (large-cap)
iShares Core S&P Mid-Cap ETF	IJH	Equity (mid-cap)
iShares Core S&P Small-Cap ETF	IJR	Equity (small-cap)
Invesco Optimum Yield Diversified Commodity Strategy No K-1 ETF	PDBC	Commodities ETF
Vanguard Intermediate-Term Corporate Bond ETF	VCIT	Corporate Bonds ETF
iShares 1-3 Year Treasury Bond ETF	SHY	Treasury ETF

Notes: This table shows 9 benchmark ETFs.

4.1.3 Risk-free Rate

By combining the six value-weighted portfolios based on book-to-market and size, Fama/ French factors are derived.[1] In this study, I used risk-free rate calculating the optimal portfolio in the rolling window to

4.2 Descriptive Statistic Results

The first analysis focuses on the descriptive statistics of the monthly returns of 15 different cryptocurrencies and of the selected main asset classes. Results are presented in Table 3 to Table 8 below.

4.2.1 Descriptive Statistic Results for Selected Cryptocurrencies

Table 3 shows the descriptive statistics results of 15 selected cryptocurrencies:

Table 3 Descriptive Statistics of Selected Cryptocurrencies

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
BTC	64	9.44%	25.11%	-36.41%	-7.63%	5.97%	28.15%	69.63%	106.04%	0.41	-0.39	6.21%
ETH	64	17.15%	47.11%	-53.64%	-16.44%	8.22%	39.96%	216.35%	269.99%	2.00	6.32	21.84%
DOGE	64	32.44%	121.99%	-53.15%	-17.10%	-0.24%	29.85%	694.41%	747.56%	4.03	17.65	146.49%
LTC	64	11.18%	38.88%	-42.53%	-19.16%	3.90%	27.30%	162.76%	205.29%	1.54	3.55	14.88%
XLM	64	25.54%	99.89%	-40.36%	-23.29%	-1.92%	33.73%	608.16%	648.52%	4.14	20.52	98.22%
ETC	64	15.72%	52.45%	-57.36%	-18.23%	2.74%	27.94%	171.30%	228.66%	1.65	2.26	27.08%
XMR	64	11.12%	44.16%	-44.34%	-11.96%	1.17%	17.40%	252.45%	296.79%	2.95	13.47	19.20%
NEO	64	27.20%	110.59%	-62.38%	-19.31%	-0.75%	31.50%	751.42%	813.80%	5.03	30.40	120.39%
ZEC	64	8.11%	41.04%	-51.43%	-21.80%	-3.04%	32.46%	152.86%	204.29%	1.31	2.36	16.58%
WAVES	64	22.72%	74.62%	-42.29%	-19.34%	-2.62%	36.33%	397.23%	439.51%	2.71	9.87	54.81%
DASH	64	12.04%	48.28%	-47.67%	-20.97%	-2.69%	27.43%	182.62%	230.29%	1.84	3.80	22.94%
XEM	64	20.09%	77.43%	-48.48%	-21.77%	-1.05%	24.70%	356.18%	404.66%	2.64	7.64	59.01%
DCR	64	20.56%	83.52%	-49.91%	-15.23%	1.67%	19.95%	490.19%	540.10%	4.24	20.55	68.67%
SYS	64	19.90%	62.69%	-56.57%	-19.28%	2.93%	32.66%	230.34%	286.90%	1.53	2.40	38.69%

[1] See Fama and French (1993) for the whole description of the factor returns.

SC	64	24.59%	95.42%	-56.26%	-25.68%	3.68%	32.51%	499.14%	555.40%	3.59	15.13	89.64%

Notes: This table presents the descriptive statistic results of fifteen Cryptocurrencies according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The sector data are taken from Coinmarketcap.com, and the sample period is from 2016.10 to 2022.03. All cryptocurrency data are changed into monthly returns and the descriptive statistic results are rounded to 2 decimals.

There are 64 variables for each kind of monthly cryptocurrency return, these currencies exhibit similar mean and median results. The standard deviation values are quite different, and most of them reached a high level, which means that the data for these cryptocurrencies are very volatile. For example, Dogecoin (DOGE) and Neo (NEO) are very volatile, with standard deviations above 100%. The Dogecoin (DOGE) has the highest standard deviation reaching 1.22. The interquartile deviation (mean, max and min) indicates that the data in the middle are more concentrated. Moreover, the range of Dogecoin (DOGE), Stellar (XLM), Neo coin (NEO), Decred (DCR), and Siacoin (SC) are much higher than those of other currencies, being greater than 4.9.

All cryptocurrencies are of a Positively skewed distribution skewed to the right; all but Bitcoin are highly skewed, the Coefficient of Neo coin (NEO) is extremely high and reaches 5.031. Except for BTC, all the values of kurtosis are above 0, which means most of them to have a leptokurtic distribution with a high degree of peakedness (the excess kurtosis suggests leptokurtic behavior), and Bitcoin has a platykurtic distribution. There is an extreme peak on the Neo coin (NEO) as it reaches 30.396, the peakednesses of Dogecoin (DOGE), Stellar (XLM), Neo coin (NEO), and Decred (DCR) are quite high.

4.2.2 Descriptive Statistic Results for Benchmark Portfolio

Table 4 below shows the descriptive statistics results of the benchmark portfolio:

Table 4 Descriptive Statistics of 9 ETFs

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
GLD	64	0.82%	3.67%	-7.15%	-1.62%	-0.03%	2.96%	10.79%	17.94%	0.40	0.10	0.13%
SHV	64	0.08%	0.13%	-0.12%	-0.00%	0.04%	0.16%	0.60%	0.72%	1.64	3.67	0.00%
AGG	64	0.19%	1.03%	-2.81%	-0.48%	0.10%	0.70%	2.78%	5.59%	0.03	0.64	0.01%
SPY	64	1.38%	4.51%	-13.00%	0.02%	1.88%	3.48%	13.36%	26.36%	-0.54	1.63	0.20%
IJH	64	1.07%	5.52%	-20.72%	-0.77%	1.63%	3.61%	14.81%	35.52%	-0.93	3.80	0.30%
IJR	64	1.06%	6.03%	-22.92%	-2.12%	1.80%	3.82%	18.22%	41.13%	-0.87	4.02	0.36%
PDBC	64	1.33%	10.41%	-30.64%	-2.50%	1.18%	4.41%	65.85%	96.49%	3.31	24.41	1.07%
VCIT	64	0.29%	1.67%	-7.28%	-0.37%	0.21%	1.03%	5.13%	12.40%	-1.03	6.53	0.03%
SHY	64	0.08%	0.38%	-1.40%	-0.09%	0.01%	0.21%	1.26%	2.66%	-0.10	4.19	0.00%

Notes: This table presents descriptive statistics of nine ETFs. The sector data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the sample period is from 2016.12 to 2022.03. All ETF data are changed into monthly returns and the descriptive statistic results are rounded to 2 decimals.

Results presented in Table 5 show that all ETFs have similar mean, median, and standard deviation. The Commodities ETF(PDBC) has the largest standard deviation reaching 10.41%. The interquartile deviation (mean, max and min) indicates that the data in the middle are more concentrated than in tails. The standard deviation values are all relatively small, indicating that the data for these main asset classes are not very volatile. Moreover, the range of PDBC is much higher than those of others, reaching 96.49%.

Half of the main asset classes are positively skewed. The Equity ETF (Including Large, Mid, and Small Cap: SPY, IJH, IJR), Corporate Bonds ETF (VCIT), and Treasury ETF (SHY) are skewed to the left. Money Market ETF (SHV), Corporate Bonds ETF (VCIT), and Commodities ETF (PDBC) are highly skewed; the Coefficient of PDBC is extremely high and reaches 3.310.

All kurtosis measures are above 0, which means they all have a leptokurtic distribution with a high degree of peakedness (the excess kurtosis suggests leptokurtic behavior); There is an extreme peak on the Commodities ETF (PDBC) as it reaches 24.41.

4.2.3 Correlation of 15 Cryptocurrencies and of the Main Asset Classes

The coefficient of correlation is a statistical indicator of the closeness of the relationship between two variables, and it ranges from 1 to -1. A value of 1 indicates a perfect linear correlation between the two variables, a value of -1 indicates a perfect negative correlation between the two variables, and a value of 0 indicates no correlation at all. The correlation is weaker the closer the data gets to zero.

Table 5 shows the Correlation coefficient matrix diagram:

Table 5 Correlation matrix of 15 Cryptocurrencies

	BTC	**ETH**	**DOGE**	**LTC**	**XLM**	**ETC**	**XMR**	**NEO**	**ZEC**	**WAVES**	**DASH**	**XEM**	**DCR**	**SYS**	**SC**
BTC	1.00														
ETH	0.54	1.00													
DOGE	0.26	0.46	1.00												
LTC	0.67	0.66	0.41	1.00											
XLM	0.56	0.65	0.53	0.58	1.00										
ETC	0.45	0.65	0.45	0.57	0.50	1.00									
XMR	0.67	0.58	0.30	0.66	0.43	0.53	1.00								
NEO	0.30	0.41	0.19	0.47	0.26	0.23	0.45	1.00							
ZEC	0.62	0.78	0.44	0.70	0.63	0.71	0.62	0.42	1.00						
WAVES	0.43	0.63	0.36	0.49	0.70	0.51	0.48	0.33	0.62	1.00					
DASH	0.61	0.63	0.22	0.63	0.34	0.68	0.72	0.33	0.70	0.36	1.00				
XEM	0.53	0.65	0.39	0.76	0.77	0.42	0.53	0.30	0.60	0.67	0.45	1.00			
DCR	0.17	0.63	0.17	0.38	0.18	0.35	0.29	0.18	0.35	0.22	0.51	0.35	1.00		

SYS	0.48	0.56	0.36	0.72	0.50	0.39	0.44	0.37	0.59	0.42	0.42	0.58	0.27	1.00	
SC	0.47	0.70	0.56	0.64	0.88	0.45	0.42	0.39	0.67	0.70	0.34	0.78	0.33	0.55	1.00

Notes: This table presents the correlation coefficient matrix of fifteen Cryptocurrencies. The sector data are taken from Coinmarketcap.com, and the sample period is from 2016.10 to 2022.03. All cryptocurrency data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

It can be observed that the highest correlation among these pairs is between Siacoin (SC) and Stellar (XLM) at 0.8839. Decred (DCR) and Dogecoin (DOGE) have the lowest correlation at 0.1691. While most of the others are at a relatively medium level between 0.4 to 0.7. The Zcash (ZEC) and Decred (DCR) have significantly lower correlation coefficients with other virtual currencies, whereas Ethereum (ETH) and Litecoin (LTC) are higher.

The following table presents the correlation between returns on benchmark assets：

Table 6 Correlation Coefficient of Benchmark Portfolio

	GLD	**SHV**	**AGG**	**SPY**	**IJH**	**IJR**	**PDBC**	**VCIT**	**SHY**
GLD	1.00								
SHV	0.14	1.00							
AGG	0.38	0.37	1.00						
SPY	0.14	-0.06	0.08	1.00					
IJH	0.08	-0.13	0.02	0.93	1.00				
IJR	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	0.29
SHY	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

This table presents the correlation coefficient matrix of 9 ETFs. The sector data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the sample period is from 2016.12 to 2022.03. All ETF data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

As the correlation coefficient matrix diagram shows, the highest correlation among these pairs is between the Mid Cap Equity (IJH) and the Small Cap Equity (IJR) at 0.9658(**), they are significantly correlated. The Commodities ETF (PDBC) and Treasury ETF (SHY) have the lowest significant correlation at –0.3893. While most of the others are at a relatively medium level between 0.5 to 0.7. The Treasury ETF (SHY) has a significantly lower correlation coefficient with the Equity ETF (IJH& IJR) and the Commodities ETF (PDBC) than with others.

4.2.4 Correlation of Two Main Cryptos with the Main Assets

In this section I show the correlation tables for two benchmark portfolios that each incorporate a representative selection of major cryptocurrencies. The cryptocurrencies selected are Bitcoin (BTC) and Ethereum (ETH), which are two of the top cryptocurrencies in terms of market capitalization and trading volume.

Table 7 Correlation Coefficient of Benchmark Portfolio with BTC

	BTC	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
BTC	1.00									
GLD	0.10	1.00								
SHV	-0.19	0.14	1.00							
AGG	0.14	0.38	0.37	1.00						
SPY	0.27	0.14	-0.06	0.08	1.00					
IJH	0.27	0.08	-0.13	0.02	0.93	1.00				
IJR	0.22	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	0.01	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.23	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.06	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

Notes: This table presents the correlation coefficient matrix of a Bitcoin portfolio consist of Bitcoin and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Bitcoin data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

As shown in the correlation tables above, the portfolio with Bitcoin in it (BTC portfolio) has the highest correlation between the Mid Cap Equity (IJH) and the Small Cap Equity (IJR) at 0.9658, which is the same as the benchmark portfolio. Bitcoin has a relatively low correlation with the other main asset classes, it even shows a negative correlation with the Money Market ETF (SHV) and with the Treasury ETF (SHY). The Commodities ETF (PDBC) has the weakest correlation with Bitcoin, with a value close to 0.01 implying that the two are barely correlated.

Table 8 Correlation Coefficient of Benchmark Portfolio with ETH

	ETH	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
ETH	1.00									
GLD	0.12	1.00								
SHV	-0.17	0.14	1.00							
AGG	0.12	0.38	0.37	1.00						
SPY	0.17	0.14	-0.06	0.08	1.00					
IJH	0.13	0.08	-0.13	0.02	0.93	1.00				
IJR	0.09	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.04	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.18	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.04	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

Notes: This table presents the correlation coefficient matrix of a Ethereum portfolio consist of Ethereum and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the

Ethereum data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

As for the ETH portfolio (portfolio with Ethereum in it), ETH even has a lower correlation with the other main asset classes than BTC, most of the values are at a relatively low level between 0.1 to 0.2. The Money Market ETF (SHV), the Commodities ETF (PDBC), and the Treasury ETF (SHY) are negatively correlated with ETH. The weakest correlation is between PDBC and ETH at -0.0362.

Chapter 5
Rolling Window Optimization

The advantage of using a rolling window is to show how asset allocations change, and how virtual currencies move over time. I construct an optimal portfolio consisting of Bitcoin or other virtual currencies) and representative ETF funds across different investment sectors by maximizing the mean-variance approach of the Sharpe ratio. The range of data used is October 2016 to July 2022, and a 24-month (two-year) estimation window is estimated for each benchmark portfolio return that incorporates virtual currencies to visually chose the optimal weights and the trend in portfolio returns.

This study uses a window of w=24 months to calculate the optimal weights, rolling forward one month at a time. This results in n-w+1 windows (where n=86, w=24) so that for each virtual currency portfolio 40 optimal portfolio weights are obtained, and the resulting weights are multiplied by the out-of-sample one-month returns (the optimal weight for the i_{th} estimated window multiplied by the return for the $(i + w + 1)_{th}$ month), weighted to calculate the portfolio return for each period. Performance measures such as the Sharpe ratio and maximum drawdown are calculated on top of the resulting out-of-sample portfolio returns. In this case, the maximized Sharpe ratio is not calculated using the raw data, but by subtracting the current month's risk-free rate from the data obtained from Portfolio Returns.

I chose two years as the window because shorter windows do not have enough data points to analyze longer time scales, while windows longer than two years do not allow for sufficient results to be analyzed in the time horizon of the data available.

This Chapter mainly presents the results of the optimal portfolios with different cryptocurrencies based on the rolling window approach, including the correlation between each cryptocurrency and the main asset classes changing over time, the optimal weights for the cryptocurrency portfolio, as well as the values of the optimal portfolio changing over time, etc.

5.1 Results of Optimal Portfolio Change Over Time

5.1.1 Correlation between Bitcoin and Other Main Asset Classes Change Over Time

The figure below shows a line figure of the correlation between Bitcoin versus other ETF assets over time:

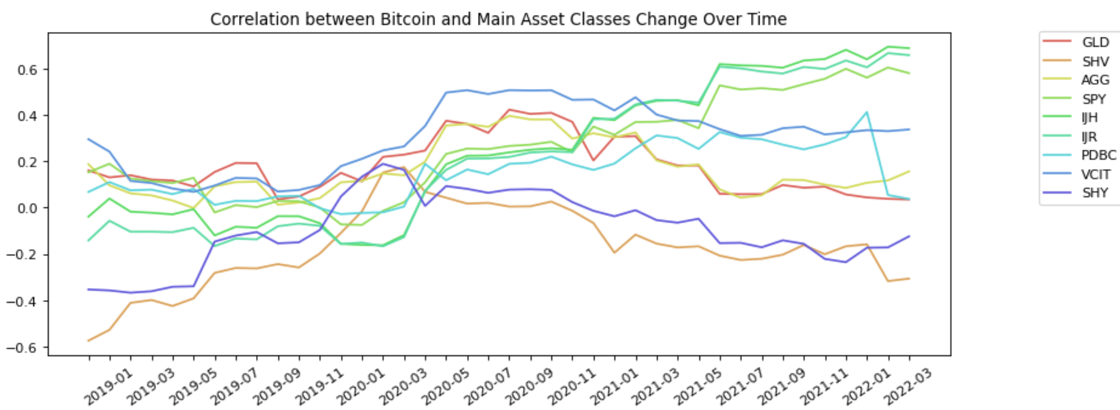

Figure 2 Correlation between Bitcoin versus Other ETF Assets Over Time

Notes: This figure presents the correlation coefficient lines between Bitcoin versus other 9 ETF assets changing over time. Each correlation coefficient between Bitcoin and any ETF fund at any point of time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.

In terms of values, the closer the value of the correlation is to 1, the greater the degree of homogeneity of the two variables. If the value is positive, then the two variables have the same tendency to take on the same value; conversely, the two variables have opposite tendencies to take on the same value. It can be seen that the correlation between Bitcoin and other assets fluctuates between -0.6 and 0.6 throughout the time horizon and has a relatively obvious positive growth overall around early 2020. Most of the correlations increase over time, becoming more correlated after the correlation coefficient approaches 0 (no correlation) in March 2020. The correlations between Bitcoin with Treasury ETF (SHY) and money market ETFs (SHV) are most times negative and the upward trend of the correlation coefficient turns down on February 2020.

5.1.2 Optimal Portfolio Weights for Bitcoin Portfolio Change Over Time

Figure 3 shows a trending figure of the optimal portfolio weights of a virtual currency portfolio over time, using Bitcoin as an example.

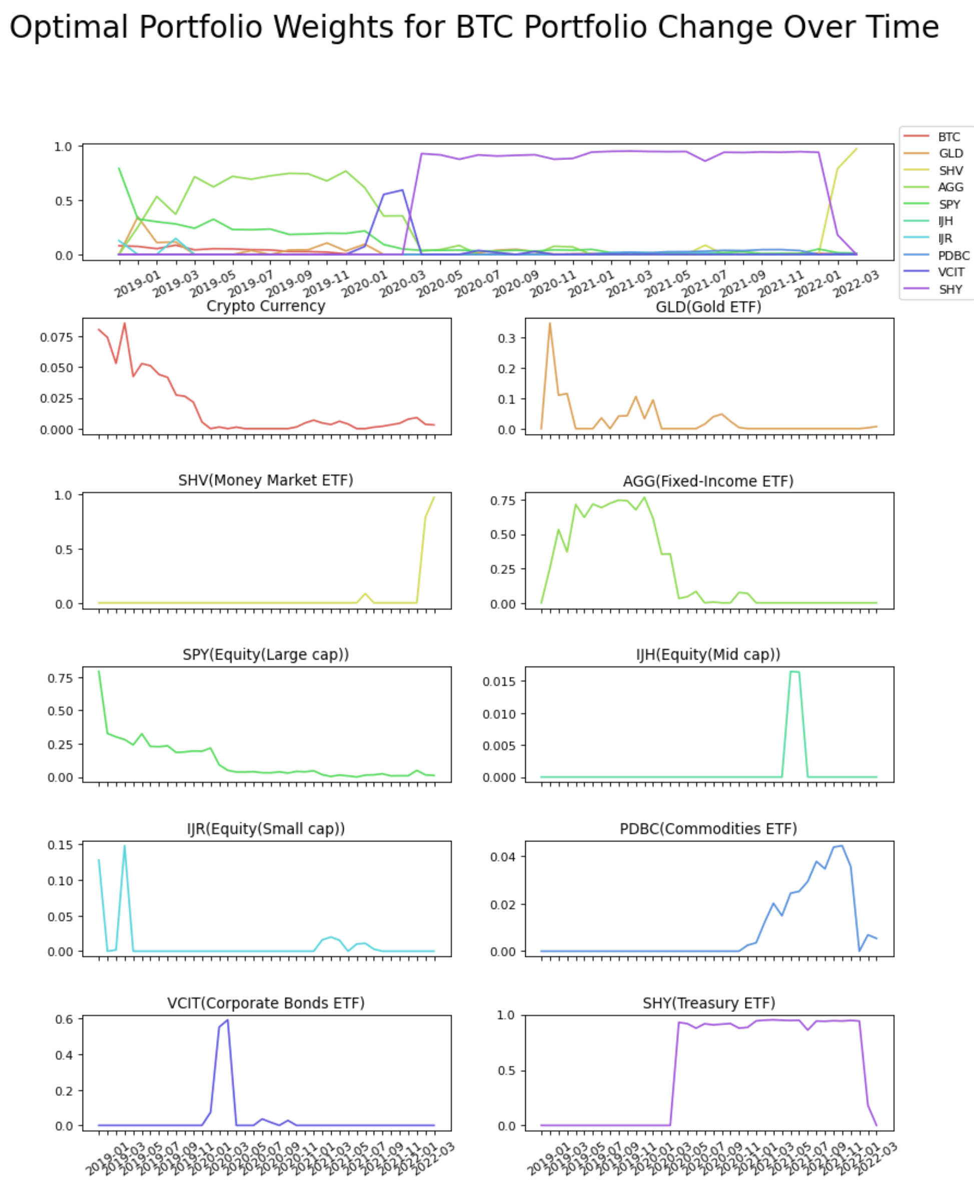

Figure 3 Optimal Portfolio Weights for Bitcoin Portfolio Change Over Time

Notes: This figure presents the optimal weight lines for Bitcoin and other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.

The optimal proportion of virtual currencies in the portfolio has been relatively small, remaining between 0% and 8.5%. Over time, the optimal weighting of cryptocurrencies continues to decline to close to zero in 2019, as investors adjust to the share of highly volatile assets like virtual currencies following the onset of the global pandemic. Fixed-income ETFs (AGG) and Large Cap Equity ETFs (SPY) make up the bulk of the portfolio until March 2020, after which Treasury ETFs (SHY) become the largest share of assets, followed by Money Market ETFs (SHV) taking the major share by the end of 2021. The inclusion of BTC has not had a significant impact on portfolio returns since early 2020.

The results of this paper for the optimal weights line chart for a portfolio consisting of 14 additional virtual currencies selected are shown in the appendix.

Overall, cryptocurrencies have very low weighting values across all 15 portfolios created with the addition of virtual currencies. For example, prior to COVID-19, the optimal weight for the BTC portfolio was 0.0855, suggesting that of a $1 BTC portfolio, 8.5 cents should be invested in BTC and 91.5 cents in other ETFs. These results are consistent with Guesmi et al. (2019) and Akhtaruzzaman et al. (2021), which find that cryptocurrencies should have very little weight in a portfolio.

This is corroborated by the results shown in the chart below.

5.1.3 Portfolio Returns for BTC Portfolio Compared with Benchmark Portfolio

The optimal portfolio returns are obtained by multiplying the optimal weights obtained from the rolling panel with the out-of-sample one-month returns and then weighting them by each asset. As an example, the out-of-sample portfolio returns over time for the portfolio with the addition of Bitcoin are shown in Figure 4. The orange line shows the change in portfolio return over time for the benchmark portfolio, while the red line represents the optimal portfolio return obtained by adding BTC. The two lines are not very different, due to the fact that the optimal weighting of Bitcoin obtained in the above calculation is only relatively high until the end of 2019, with the resulting impact on the portfolio returns.

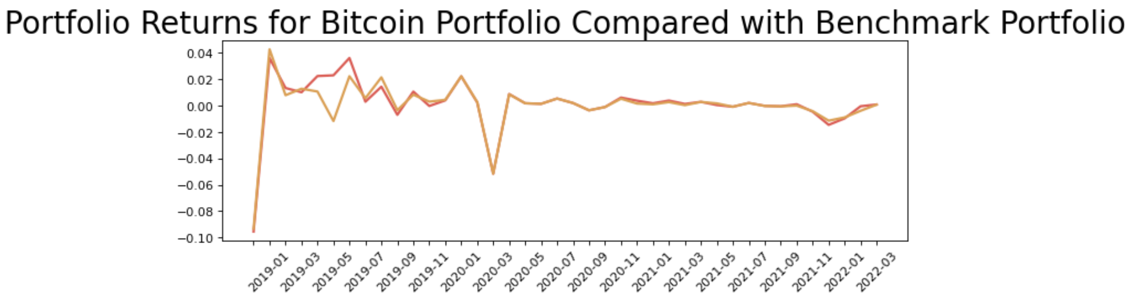

Figure 4 Portfolio Returns for BTC Portfolio Compared with Benchmark Portfolio

Notes: This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Bitcoin portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Bitcoin portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The correlations shown in the figures above, the out-of-sample portfolio return comparison figures, and the performance statistics for this optimal portfolio are applications of the Bitcoin portfolio. Similar calculations were done for the 14 other virtual currencies selected for the analysis and calculations in this paper and the resulting line figure results are shown in the appendix.

The trends in the correlation coefficients of the 15 cryptocurrencies with the main asset classes of the benchmark portfolio vary considerably. Most of the correlation coefficients have similar trends over time, gradually changing from negative to positive overall and close to zero in early 2020. Treasury ETFs (SHY) and Money Market ETFs (SHV) show negative correlations with most virtual currencies over the entire time horizon. The results show that the optimal proportion of all virtual currencies is quite low in the portfolio, with Bitcoin (BTC) and Litecoin (LTC) having the highest weight share, peaking at around 0.075, and Neo (NEO) and Siacoin (SC) having the least impact, peaking at 0.015. The majority of cryptocurrencies show a similar downward trend in weight share, being affected to varying degrees and falling to a minimum at the point in time when the global pandemic begins. Portfolio return, therefore, differs from that of the benchmark portfolio until early 2020, after which the figure of cryptocurrency portfolio returns broadly overlaps that of the benchmark portfolio.

Descriptive statistics for the optimal portfolio return, including the benchmark portfolio as well as the 15 virtual currency portfolios, are shown in the following set of tables.

Table 9 Descriptive Statistics of Optimal Crypto Portfolio Returns

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.77	12.25	0.04%
BTC	40	0.12%	2.09%	-9.55%	-0.05%	0.18%	0.67%	3.61%	13.15%	-2.77	12.25	0.04%
ETH	40	0.04%	1.90%	-8.83%	-0.07%	0.21%	0.56%	3.29%	12.12%	-3.04	12.97	0.04%
DOGE	40	0.02%	1.99%	-9.08%	-0.17%	0.14%	0.52%	4.82%	13.90%	-2.54	12.16	0.04%
LTC	40	0.19%	2.12%	-8.98%	-0.07%	0.17%	0.56%	4.73%	13.70%	-2.04	9.47	0.04%
XLM	40	-0.10%	2.11%	-10.21%	-0.13%	0.15%	0.37%	4.72%	14.93%	-2.93	14.27	0.04%
ETC	40	0.04%	1.90%	-8.72%	-0.10%	0.16%	0.52%	3.62%	12.34%	-2.89	12.55	0.04%
XMR	40	0.03%	2.08%	-9.95%	-0.10%	0.17%	0.52%	4.21%	14.16%	-3.06	14.23	0.04%
NEO	40	0.04%	1.91%	-8.53%	-0.10%	0.15%	0.52%	4.40%	12.93%	-2.55	11.49	0.04%
ZEC	40	0.02%	2.05%	-9.89%	-0.09%	0.17%	0.54%	3.84%	13.73%	-3.17	14.61	0.04%
WAVES	40	0.09%	1.91%	-5.96%	-0.08%	0.14%	0.59%	6.04%	12.00%	-0.79	5.21	0.04%
DASH	40	0.02%	1.99%	-9.52%	-0.09%	0.17%	0.52%	3.09%	12.61%	-3.22	14.40	0.04%
XEM	40	0.04%	2.12%	-10.01%	-0.10%	0.17%	0.56%	4.69%	14.70%	-2.91	13.89	0.04%
DCR	40	0.01%	1.96%	-9.47%	-0.10%	0.16%	0.52%	3.34%	12.81%	-3.27	14.89	0.04%
SYS	40	0.12%	1.76%	-6.76%	-0.11%	0.15%	0.52%	4.55%	11.31%	-1.72	7.63	0.03%

Notes: This table presents the descriptive statistics of fifteen Cryptocurrency portfolios' monthly return, as well as the benchmark portfolio return, according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All cryptocurrency portfolio data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

These portfolio returns exhibit similar mean, median, and standard deviation values, with the Stellar (XLM) portfolio showing a negative mean. Among all 16 portfolios, Litecoin (LTC) portfolio has the highest average optimal monthly portfolio return in the 2018-2022 period (about 0.19%). The standard deviation values are all relatively small, indicating that the data for these cryptocurrency portfolios are not very volatile, with standard deviations of around 2%. Litecoin (LTC) and Nem (XEM) have the highest standard deviation reaching 2.12% and the Syscoin (SYS) has the lowest one reaching 1.76%. The interquartile deviation (mean, max and min) indicates that the data in the middle are more concentrated, however, the range of all 15 cryptocurrency portfolios' return (around 13%) is much smaller than that of 15 cryptocurrencies.

Most cryptocurrency portfolio returns are Negatively (left) skewed distribution, with only Zcash (ZEC) portfolio return not being highly skewed with skewness of -0.787; Nem (XEM) portfolio return has the lowest coefficient at -3.269. All cryptocurrency portfolios have a kurtosis above 0, which means they all have Leptokurtic distribution. All kurtosis measures are above 0, which means they all have a leptokurtic distribution with a high degree of peakedness (the excess kurtosis suggests leptokurtic behavior); There is an extreme peak on the Decred (DCR) portfolio as it reaches 14.89, the Waves portfolio has the lowest peakedness at 5.21.

Chapter 6
Further Analysis

In this section, the optimal portfolio is further analyzed by splitting the dataset by year, applying the cryptocurrency dataset as a portfolio and optimizing it, and adding the average weighted cryptocurrency as a new asset class to the benchmark portfolio.

6.1 Different levels of the expected return of cryptos

Due to various realities such as the global pandemic and recession, virtual currencies do not have a very strong impact on the portfolio over the time period calculated, so I explore whether out-of-sample portfolio returns would be significantly different under different expected returns by fixing expected returns of virtual currencies at different levels.

Still using the Bitcoin portfolio as an example, the table below shows descriptive statistics for out-of-sample portfolio returns, including mean, variance, standard deviation, kurtosis, and skewness. The Bitcoin historical prices are replaced by the different levels (5%, 10%, 15%, 20%) of expected returns and recalculated, these new portfolios are also present in the Table below.

Table 10 Descriptive Statistics of Bitcoin Portfolio (Different Levels)

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.77	12.25	0.04%
Historical	40	0.12%	2.09%	-9.55%	-0.05%	0.18%	0.67%	3.61%	13.15%	-2.71	13.57	0.04%
Level 5%	40	0.11%	1.97%	-9.27%	-0.09%	0.16%	0.55%	4.05%	13.32%	-2.37	12.52	0.04%
Level 10%	40	0.22%	2.05%	-9.44%	-0.06%	0.15%	0.71%	4.27%	13.71%	0.99	2.65	0.03%
Level 15%	40	0.47%	1.72%	-3.97%	-0.15%	0.22%	0.75%	5.42%	9.40%	0.87	8.10	0.02%
Level 20%	40	0.26%	1.59%	-4.80%	-0.22%	0.25%	0.73%	6.66%	11.46%	0.36	-0.45	4.65%

BTC itself	40	8.38%	21.83%	-35.35%	-7.07%	5.97%	26.56%	60.25%	95.60%	1.55	1.29	0.06%
BTCWeights	40	1.68%	2.47%	0.00%	0.09%	0.40%	2.65%	8.55%	8.55%	0.59	-1.52	0.00%

Notes: This table presents the descriptive statistics of the benchmark portfolio as well as the Bitcoin portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical bitcoin returns, while rows three to six show the descriptive statistics for the most available portfolio returns with bitcoin's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Bitcoin itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The optimal asset portfolio returns for Bitcoin have similar means, quartiles, and standard deviations to the benchmark portfolio, which corroborates the near-overlapping portfolio return folds of Figure 4. As the specified level of expected return increases from 5% to 20%, the spread of the data from the mean instead decreases and the mean becomes larger.

The table above shows the descriptive statistics for the Bitcoin portfolio, and the corresponding results for the other 14 virtual currencies selected are shown in the appendix (descriptive statistics for the virtual currencies themselves and the optimal weights obtained from their historical data).

6.2 Split on a Yearly Basis

To confirm in more detail whether the results derived from the selected data have been affected by events such as global pandemics or economic recessions, I divide the data results into years after the out-of-sample portfolio returns are obtained and calculate the Sharpe ratio for each year separately.

6.2.1 Descriptive Statistics of Optimal Crypto Portfolio

Table 11 shows the Sharpe ratios of the optimal portfolio returns for cryptocurrencies and the Sharpe ratios before and during COVID-19 after splitting by year.

Table 11 Sharpe Ratio for Crypto Portfolios

	Sharpe Ratio	Sharpe Ratio_2019	Sharpe Ratio_2020	Sharpe Ratio_2021	Sharpe Ratio_2022
Benchmark	-0.03	0.64	-0.05	-0.17	-1.05
BTC	0.03	0.94	-0.04	-0.14	-0.68
ETH	-0.02	0.90	-0.04	-0.12	-0.72
DOGE	-0.03	0.55	-0.04	-0.07	-0.93
LTC	0.06	0.88	-0.05	-0.17	-0.85
XLM	-0.08	0.35	-0.05	-0.17	-0.85
ETC	-0.02	0.79	-0.05	-0.17	-0.82
XMR	-0.02	0.76	-0.05	-0.13	-0.96
NEO	-0.02	0.66	-0.06	-0.16	-0.85
ZEC	-0.03	0.78	-0.05	-0.18	-0.85
WAVES	0.01	0.30	-0.02	-0.16	-0.24
DASH	-0.02	0.83	-0.05	-0.17	-0.85
XEM	-0.02	0.71	-0.05	-0.15	-0.85
DCR	-0.03	0.80	-0.05	-0.15	-0.83
SYS	0.03	0.73	-0.05	-0.18	-1.07
SC	-0.03	0.62	-0.04	-0.16	-0.77

Notes: This table presents the Sharpe ratios of fifteen Cryptocurrency portfolios as well as the benchmark portfolio. Each portfolio is split and recalculated on a yearly basis, columns 3 to 6 present the Sharpe ratio results for them. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

Due to the small number of years covered by the results, I split the data on a yearly basis to obtain the Sharpe ratio for each year separately. The investor's benchmark portfolio has a Sharpe ratio of -0.03, which indicates that the fund has no generated excess return: for every 1% increase in risk in the benchmark portfolio, its excess return decreases by 3%. In contrast, with the exception of Siacoin (SC), the Sharpe ratios of the returns of the other portfolios that incorporate virtual currencies have improved marginally. While most virtual currency portfolios still have negative Sharpe ratios, the addition of Bitcoin, Litecoin (LTC), Waves (WAVES), and Syscoin (SYS) turned their respective portfolio Sharpe ratios from negative to positive. The largest increase was seen in Litecoin (LTC) portfolio, where the Sharpe ratio improved from -0.0298 to 0.0272.

After splitting the returns by year, the Sharpe ratios obtained for each year separately show that their values are decreasing every year, with all portfolios having a positive Sharpe index in 2019, while after this the ratios shift to negative and decrease year on year. Compared to the benchmark portfolios, most of the portfolios with the inclusion of virtual currencies still showed a small increase. For example, in 2019, all portfolios except Dogecoin (DOGE), Stellar (XLM), Waves (WAVES), and Siacoin (SC)had higher Sharpe ratios than the benchmark portfolio's Sharpe index in 2019. In 2020, while the Sharpe ratios of all portfolios as a whole are lowered to the plural, most are still higher than the benchmark portfolio, while the Monero (XMR), Neo coin (NEO), Zcash (ZEC), Dash coin (DASH), and Syscoin (SYS) portfolios that below it actually have Sharpe ratios very close to it. ditto for 2021. only Syscoin (SYS) has a portfolio with a Sharpe ratio below the benchmark portfolio's Sharpe ratio in 2022.

The results show that the inclusion of virtual currencies in a portfolio can help to improve the performance of the portfolio. Combined with the previous analysis, it can be concluded that virtual currencies may help to reduce risk, but help to increase returns. This is related to the inherently high volatility nature of virtual currencies and therefore the optimal proportion of virtual currencies is not too high for the risk-averse. Although overall the Sharpe ratio of the portfolio in which SC is invested has decreased, its future performance may also change as the out-of-sample return data does not cover a long time period (less than five years).

In summary, the results for the 016-2022 period suggest that Bitcoin and other virtual currencies can be a good investment class for diversified portfolios. This is similar to the results obtained by Hoang, Zhu, Xiao, and Wong (2018).

6.2.2 Maximum Drawdown Results for Crypto Portfolios

Table 12 Maximum Drawdown Results for Crypto Portfolios

	Benchmark	**Historical**	**Level 5%**	**Level 10%**	**Level 15%**	**Level 20%**	**crypto itself**
BTC	-9.33%	-9.55%	-9.27%	-9.44%	-4.97%	-6.35%	-40.53%
ETH	-9.33%	-8.83%	-9.24%	-9.03%	-8.81%	-8.81%	-55.41%
DOGE	-9.33%	-9.08%	-9.30%	-9.23%	-9.16%	-9.08%	-60.55%
LTC	-9.33%	-8.98%	-9.27%	-9.22%	-9.18%	-8.77%	-67.85%
XLM	-9.33%	-10.21%	-9.33%	-9.35%	-9.39%	-9.42%	-74.25%
ETC	-9.33%	-8.72%	-9.24%	-9.09%	-8.93%	-8.74%	-63.38%
XMR	-9.33%	-9.95%	-9.44%	-9.52%	-9.69%	-9.98%	-65.07%
NEO	-9.33%	-8.53%	-9.32%	-9.31%	-9.31%	-9.30%	-79.68%
ZEC	-9.33%	-9.89%	-9.64%	-9.94%	-10.39%	-10.58%	-73.14%
WAVES	-9.33%	-5.96%	-8.53%	-7.88%	-7.25%	-6.63%	-81.01%
DASH	-9.33%	-9.52%	-9.35%	-9.40%	-9.45%	-9.50%	-75.06%
XEM	-9.33%	-10.01%	-9.35%	-9.36%	-9.38%	-9.39%	-83.04%
DCR	-9.33%	-9.47%	-9.35%	-9.37%	-9.38%	-9.40%	-70.01%

SYS	-9.33%	-6.76%	-9.12%	-8.97%	-8.82%	-8.74%	-76.95%
SC	-9.33%	-9.68%	-9.34%	-9.34%	-9.35%	-9.35%	-76.36%

Notes: This table presents the maximum drawdown results of fifteen Cryptocurrency portfolios. The second column shows the results calculated using real historical cryptocurrency returns, while columns three to six show the maximum drawdown for the most available portfolio returns with cryptocurrency's expected return set at 5%, 10%, 15%, and 20% respectively. The last column shows the results in data form for the maximum drawdown of cryptocurrency itself. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The maximum drawdown results for each of the 15 virtual currency portfolios and the benchmark portfolio are shown in the table above. This risk indicator is used to describe the maximum loss an investor could face, for example, the benchmark portfolio experienced a maximum loss of 9.33% over the time period 2019 to 2022, while the maximum drawdown of Waves (WAVES) over this time period was only 5.96%, outperforming the benchmark portfolio. Of all the virtual currency portfolios, Ethereum (ETH), Dogecoin (DOGE), Litecoin (LTC), Ethereum-Classic (ETC), Neo coin (NEO) and Waves (WAVES) have lower maximum drawdown than the benchmark portfolio, but the MMD values of the other virtual currency portfolios are actually very close to the benchmark portfolio's MMD. For investors, paying attention to a portfolio's MMD can help them understand the portfolio's ability to control risk and know the maximum loss they are facing.

It can be clearly seen that the maximum drawdown of any single virtual currency over this time period is much higher than the maximum percentage drawdown of any portfolio, which confirms that virtual currencies are characterized by high risk and high volatility.

6.3 Two other Ways

This section discusses two other ways of constructing asset portfolios: one is to consider the 15 virtual currencies as a completely new portfolio, and to perform the same steps of analysis for this all-virtual currency portfolio, i.e. to obtain the optimal weights for this portfolio by minimizing the negative value of the Sharpe ratio under a rolling window using the mean-variance method, and to calculate the out-of-sample portfolio return to obtain its Sharpe ratio, maximum drawdown and other performance measures.

The second is to equal-weight the historical data of the 15 virtual currencies and treat them as a new asset class and try to add this equal-weighted virtual currency to the benchmark portfolio for analysis.

6.3.1 All-Crypto Portfolio Optimization

The trend of the optimal weights of the virtual currency portfolio over time compared to the benchmark portfolio is shown in the figure below.

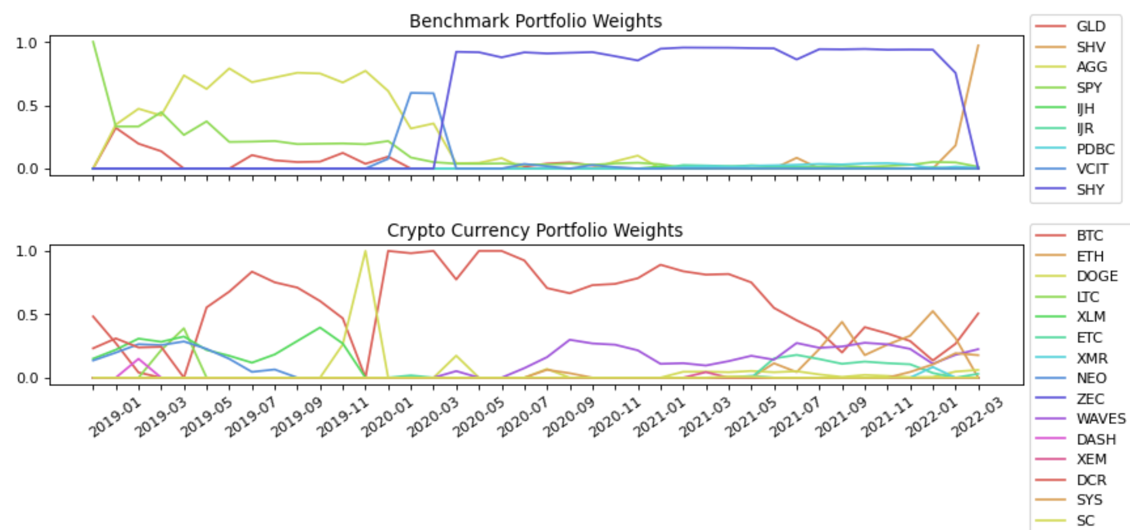

Figure 5 Trend of the Optimal Weights

Notes: These figures present the comparison of optimal weights for the benchmark portfolio and the 15 cryptocurrency portfolios changing over time. The upper figure shows the optimal weights of the 9 ETSs in the benchmark portfolio, while the second figure shows the optimal weights for the 15 cryptocurrencies of their own cryptocurrency portfolios respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). Optimal weights are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the results is from 2018.11 to 2022.03.

As can be seen, the optimal weights in the cryptocurrency portfolio have also been changing over time. With Bitcoin dominating most of the time, Ethereum (ETH), Waves (WAVES), Dogecoin (DOGE), and Stellar (XLM) all also have high optimal weights at various times. A line figure of the out-of-sample optimal portfolio returns for this portfolio is shown below, and it is clear that the portfolio is highly volatile, perhaps due to the inherently high-risk nature of virtual currencies and the fact that the virtual currencies within the portfolio do not have a very low correlation.

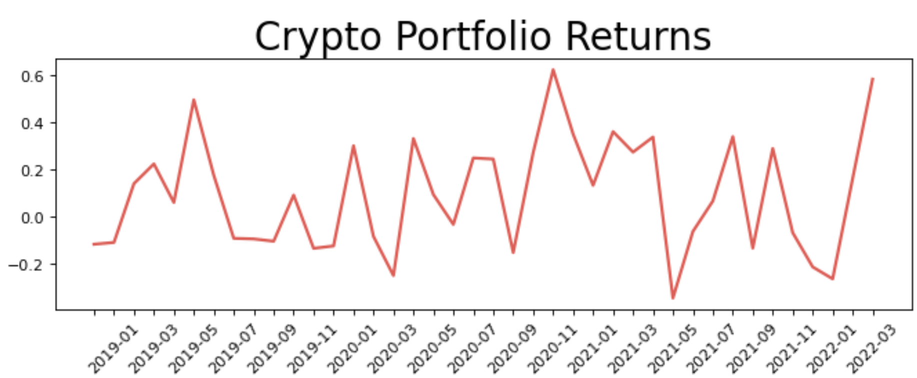

Figure 6 Cryptocurrency Portfolio Returns

Notes: This figure presents the portfolio returns for the portfolio which consists of the 15 cryptocurrencies changing over time. The cryptocurrency data are taken from Coinmarketcap.com. Optimal weights are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the results is from 2018.11 to 2022.03.

Evaluating the performance measures of the portfolio, the table below shows that the Sharpe ratio of the Virtual Currency portfolio is higher compared to the benchmark portfolio, but the maximum drawdown is also much greater than the benchmark portfolio at 47.8%. Evaluating the performance measures of the portfolio, the table below shows that the Sharpe ratio of the Virtual Currency portfolio is higher compared to the benchmark portfolio, but the maximum drawdown is also much greater than the benchmark portfolio at 47.8%.

Table 13 Performance Measures: Sharpe

	Sharpe Ratio	**Sharpe Ratio_2019**	**Sharpe Ratio_2020**	**Sharpe Ratio_2021**	**Sharpe Ratio_2022**
Benchmark	-0.029774	0.643526	-0.052527	-0.165867	-1.054191
Crypto_Portfolio_returns	0.393039	0.222299	0.667074	0.344364	0.459229

Notes: This table presents the Sharpe ratios of the portfolio which consists of the 15 cryptocurrencies as well as the benchmark portfolio. Each portfolio is split and recalculated on a yearly basis, columns 3 to 6 present the Sharpe ratio results for them. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). Sharpe ratios are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The table above shows the Sharpe ratios for the portfolio's returns, as well as the Sharpe ratios before and at COVID-19 after splitting by year. The investor's benchmark portfolio had a Sharpe ratio of -0.03, compared to the new portfolio's Sharpe ratio of 0.4. This indicates that the fund is operating with excess returns over volatility risk: for every 1% increase in risk in the benchmark portfolio, its excess returns increase by 4%.

The Sharpe ratios were obtained for each year separately after dividing the returns on an annual basis. The Sharpe ratios for all years are positive and all are higher than those of the benchmark portfolio. The results for the entire period (2016-2022) show that using 15 cryptocurrencies as a portfolio helps to improve performance.

For MMD, the benchmark portfolio experienced a maximum loss of 9.3343%, while the cryptocurrency portfolio outperformed the benchmark portfolio with a maximum loss of only 4.7802% over this timeframe.

Table 14 Performance Measures: Max Drawdown

	Benchmark	Crypto_Portfolio_returns
Max Drawdown	-0.093343	-0.478017

Notes: This table presents the maximum drawdown results of the portfolio which consists of the 15 cryptocurrencies as well as the benchmark portfolio. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). Maximum drawdowns are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

Overall, due to their own characteristics, cryptocurrency portfolios are also extremely risky and volatile, but may also offer greater return rewards and are not a good option for risk-averse investors.

6.3.2 Equal-weighted crypto asset class

The equally weighted portfolio returns of the 15 virtual currencies are treated as a new asset added to the portfolio and used for comparison with the optimal benchmark portfolio. The descriptive statistics are shown in Table 14:

Table 15 Descriptive Statistics: Equal-weighted Cryptocurrency Asset

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.011%	2.005%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.898	12.817	0.0418%
Historical	40	0.108%	2.072%	-9.58%	-0.05%	0.19%	0.66%	3.61%	13.19%	-2.728	13.621	0.0377%

Level 5%	40	0.111%	1.966%	-9.28%	-0.09%	0.16%	0.55%	4.06%	13.34%	-2.449	12.992	0.0406%
Level 10%	40	0.211%	2.041%	-9.46%	-0.06%	0.15%	0.84%	4.36%	13.82%	0.944	2.776	0.0276%
Level 15%	40	0.453%	1.681%	-3.96%	-0.16%	0.22%	0.76%	5.54%	9.50%	0.970	8.701	0.0245%
Level 20%	40	0.290%	1.584%	-4.80%	-0.27%	0.28%	0.70%	6.77%	11.57%	0.339	-0.519	4.5795%
equal_wt crypto	40	8.328%	21.672%	-33.73%	-7.85%	6.79%	25.22%	59.62%	93.36%	1.623	1.634	0.0498%
equal_wt Weights	40	1.512%	2.260%	0.00%	0.00%	0.36%	2.26%	7.99%	7.99%	0.590	-1.523	0.0001%

Notes: This table presents the descriptive statistics of the benchmark portfolio as well as the Equal-weighted Cryptocurrency portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Equal-weighted Cryptocurrency asset returns, while rows three to six show the descriptive statistics for the most available portfolio returns with the expected return of Equal-weighted Cryptocurrency asset class set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of the Equal-weighted Cryptocurrency asset class itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The Equal-weighted Cryptocurrency portfolio has 40 out-of-sample return results. After assigning different levels of expected returns to this new equally-weighted asset, the optimal asset portfolio comprises returns similar to the mean, quartiles, and standard deviation of the benchmark portfolio. As the specified level of expected return increases from 5% to 20%, the mean becomes larger.

Table 16 Performance Measures (Equal-weighted): Sharpe

	Sharpe Ratio	**Sharpe Ratio_2019**	**Sharpe Ratio_2020**	**Sharpe Ratio_2021**	**Sharpe Ratio_2022**

Benchmark Portfolio	-0.029774	0.643526	-0.052527	-0.165867	-1.054191
Historical Port	0.018589	0.966053	-0.039372	-0.147316	-0.678679
Level 5%	0.020692	0.795906	0.052140	-0.166032	-0.853771
Level 10%	0.069947	0.807080	0.211182	-0.138407	-0.623774
Level 15%	0.233602	0.607110	0.186408	-0.062524	-0.505423
Level 20%	0.140535	0.275369	0.192591	0.129802	-0.542494
equal_wt_crypto	0.385745	0.323165	0.657580	0.310264	0.009961

Notes: This table presents the Sharpe ratios of the benchmark portfolio as well as the Equal-weighted Cryptocurrency portfolio. Each portfolio is split and recalculated on a yearly basis, columns 3 to 6 present the Sharpe ratio results for them. The second row shows the results calculated using real historical Equal-weighted Cryptocurrency asset returns, while rows three to six show the Sharpe ratios for the most available portfolio returns with the expected return of Equal-weighted Cryptocurrency asset class set at 5%, 10%, 15%, and 20%, respectively. The last row shows the results in data form for the Sharpe ratio of the Equal-weighted Cryptocurrency asset class itself. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). Sharpe ratios are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

Table 17 Performance Measures (Equal-weighted): Max Drawdown

	Benchmark Portfolio	Historical Port Return	Level 5%	Level 10%	Level 15%	Level 20%	equal_wt_crypto
Max Drawdown	-0.093343	-0.095768	-0.092761	-0.094625	-0.049071	-0.063264	-0.417243

Notes: This table presents the maximum drawdown results of the benchmark portfolio as well as the Equal-weighted Cryptocurrency portfolio. The second column shows the results calculated using real historical Equal-weighted Cryptocurrency asset returns, while columns three to six show the maximum drawdown for the most available portfolio returns with the expected return of Equal-weighted Cryptocurrency asset class set at 5%, 10%, 15%, and 20% respectively. The last column shows the results in data form for the maximum drawdown of the Equal-weighted Cryptocurrency asset class itself. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). Maximum drawdowns are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

The tables above show the Sharpe ratios for the optimal returns of the portfolio, including the results for the expected returns at each level of the virtual currency and the results when broken down by year, as well as the maximum drawdown, respectively. It can be seen that the maximum drawdowns are similar for both Benchmark and Equal-weighted portfolios.

Compared with the previous results, this equally weighted cryptocurrency portfolio performs slightly better than the benchmark portfolio and the portfolio with the addition of Waves (WAVES), and slightly worse than the portfolio with Bitcoin, Litecoin (LTC), and Syscoin (SYS).

Chapter 7
Conclusion

With the development and prosperity of the virtual currency market, this new type of currency is gradually being studied in depth as a financial asset in the investment field.

For the 15 virtual currencies, the results of all portfolio optimizations are relatively similar, as they are relatively underweighted in the portfolios and therefore the out-of-sample monthly returns for each portfolio do not change dramatically. Compared to the optimization results for the benchmark portfolios without virtual currencies, the addition of virtual currencies leads to an increase in the Sharpe ratio of the portfolios, i.e., virtual currencies lead to an increase in the excess return per unit of risk of the portfolios, but with a corresponding increase in the maximum drawdown, or risk of the portfolios. It is worth noting that the virtual currency, Bitcoin (BTC) and Litecoin (LTC), have the highest weighting of all the optimal portfolios.

Due to the impact of virtual currency volatility, I set out the expected returns for different levels of virtual currencies to calculate and analyze, and the results show that the performance of each portfolio improves after removing the volatility of virtual currencies. The negative impact of the global pandemic is evident in the analysis of the performance measures of portfolio returns when the data results are split by year. A portfolio with all virtual currencies as asset classes is characterized by higher risk and higher returns; And when 15 virtual currencies are added to the portfolio as a new virtual currency after equal weighting, it outperforms most single virtual currency portfolios but slightly underperforms the portfolio in which BTC, LTC, and SYS are located.

In conclusion, virtual currencies do not make up a large proportion of a portfolio. While the high volatility of virtual currencies can add risk to a portfolio, they can also be considered a well-diversified portfolio asset given that it helps to increase returns.

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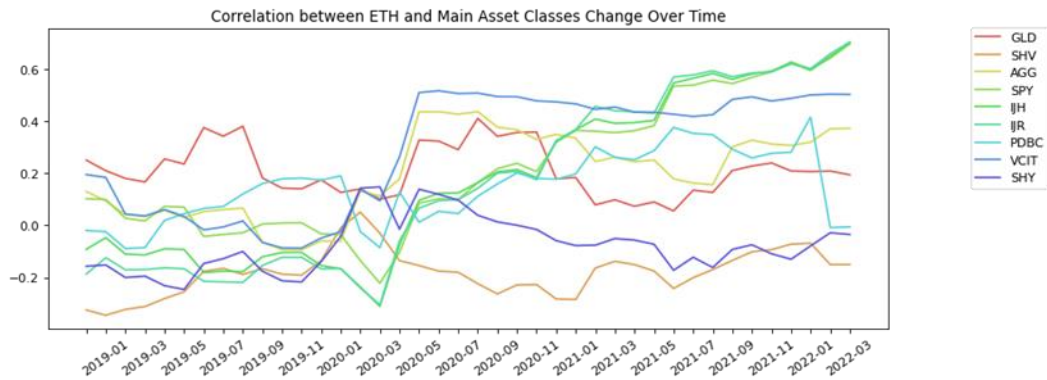
Appendix

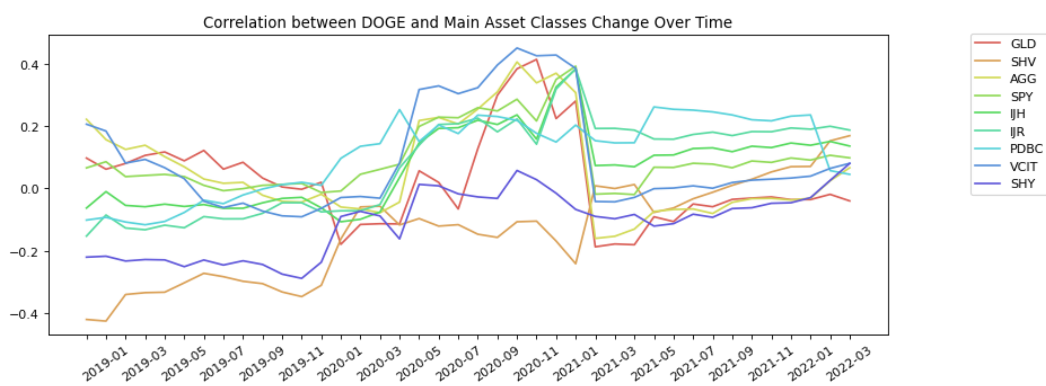
Figures

A.1 Correlation between Cryptocurrency and Other Main Asset Classes Change Over Time



A.1. 1 Correlation between Ethereum versus Other ETF Assets Over Time

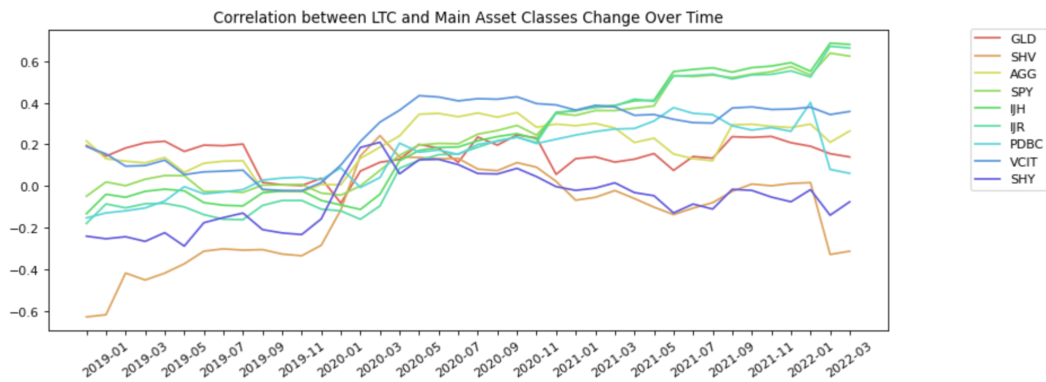
This figure presents the correlation coefficient lines between Ethereum versus the other 9 ETF assets changing over time. Each correlation coefficient between Ethereum and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



A.1. 2 Correlation between Dogecoin versus Other ETF Assets Over Time

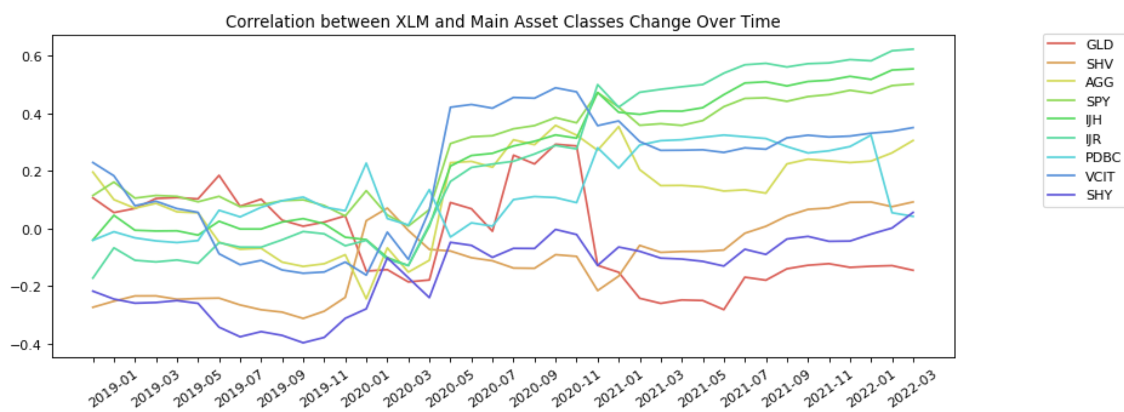
This figure presents the correlation coefficient lines between Dogecoin versus the other 9 ETF assets changing over time. Each correlation coefficient between Dogecoin and any

ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



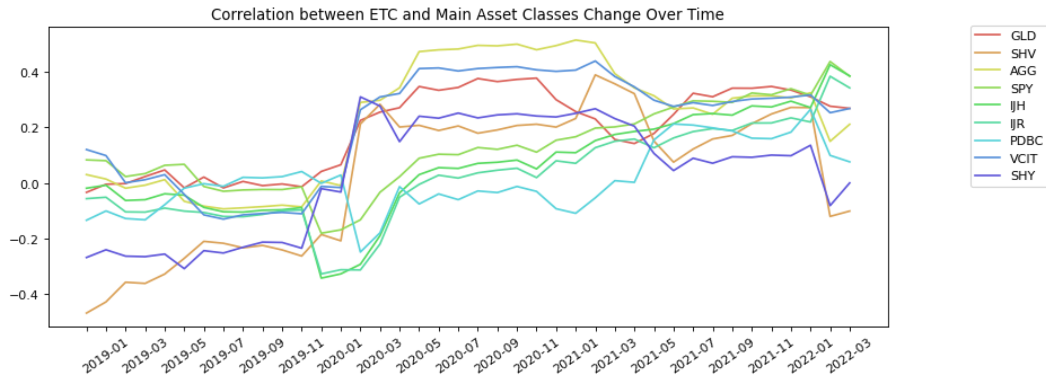
A.1. 3 Correlation between Litecoin versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Litecoin versus the other 9 ETF assets changing over time. Each correlation coefficient between Litecoin and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



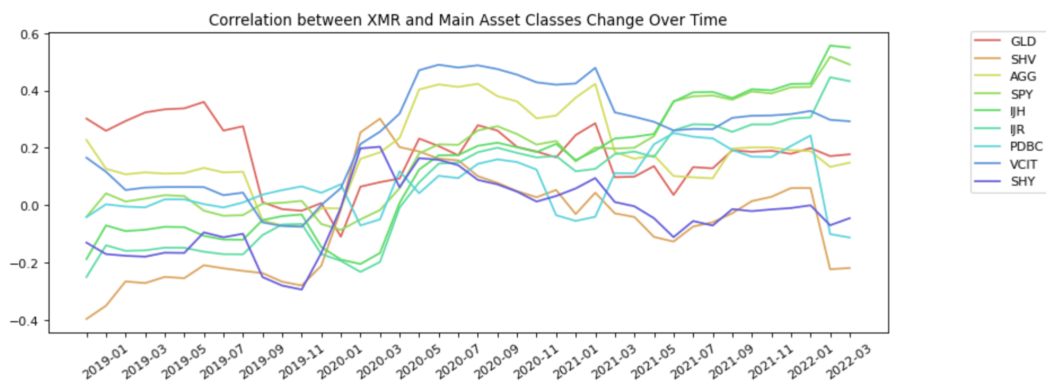
A.1. 4 Correlation between Stellar versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Stellar versus the other 9 ETF assets changing over time. Each correlation coefficient between Stellar and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



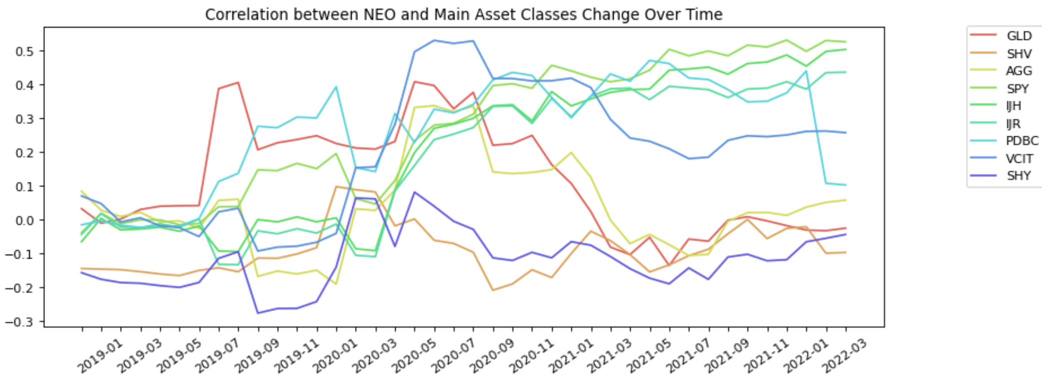
A.1. 5 Correlation between Ethereum-Classic versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Ethereum-Classic versus the other 9 ETF assets changing over time. Each correlation coefficient between Ethereum-Classic and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



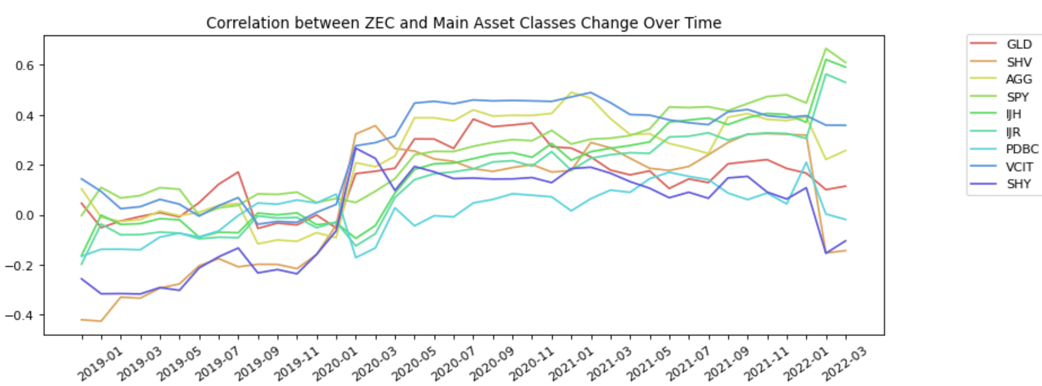
A.1. 6 Correlation between Monero versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Monero versus the other 9 ETF assets changing over time. Each correlation coefficient between Monero and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



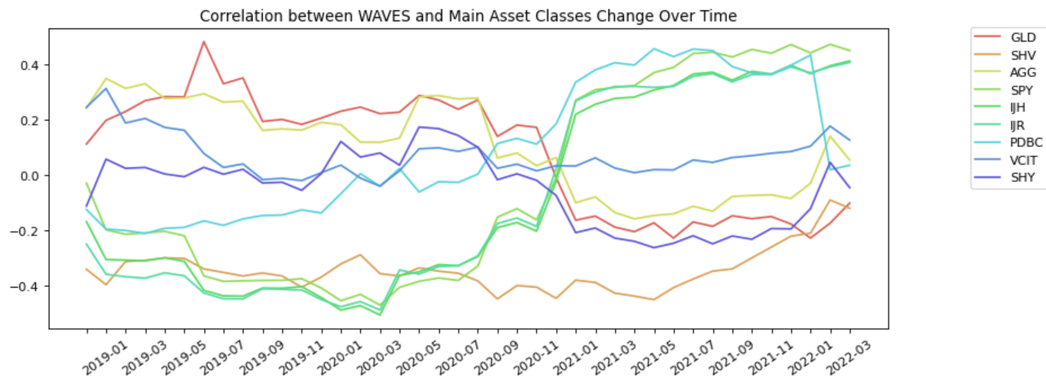
A.1. 7 Correlation between Neo versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Neo versus the other 9 ETF assets changing over time. Each correlation coefficient between Neo and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



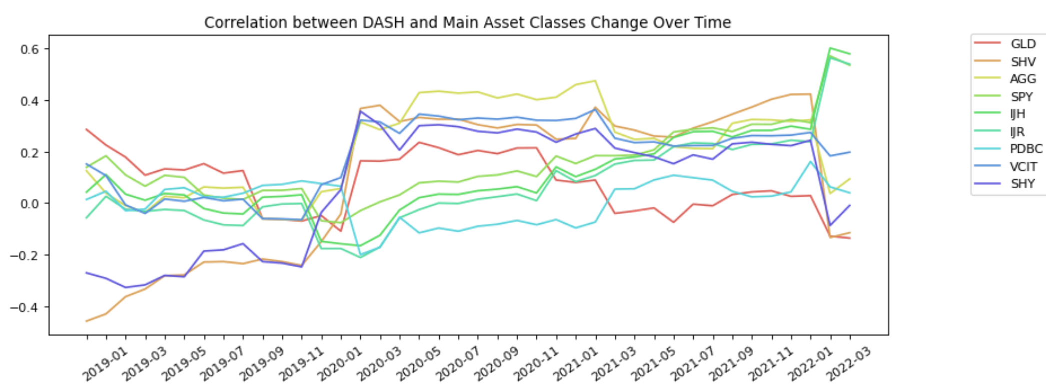
A.1. 8 Correlation between Zcash versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Zcash versus the other 9 ETF assets changing over time. Each correlation coefficient between Zcash and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



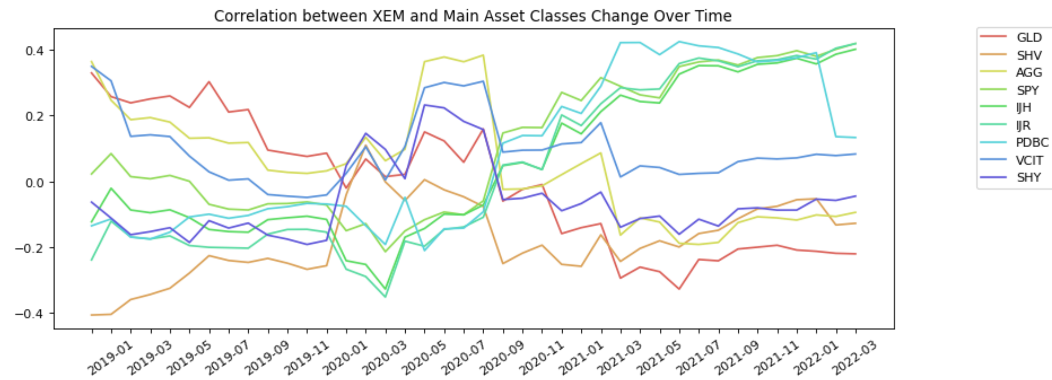
A.1. 9 Correlation between Waves versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Waves versus the other 9 ETF assets changing over time. Each correlation coefficient between Waves and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



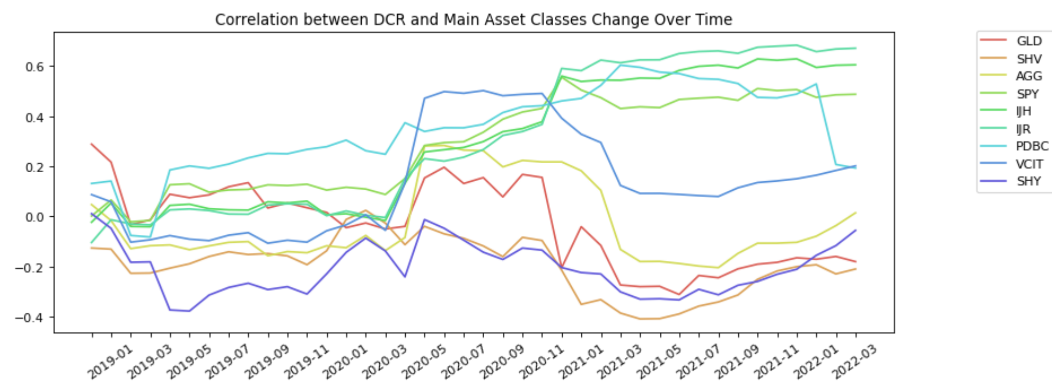
A.1. 10 Correlation between Dash versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Dash versus the other 9 ETF assets changing over time. Each correlation coefficient between Dash and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



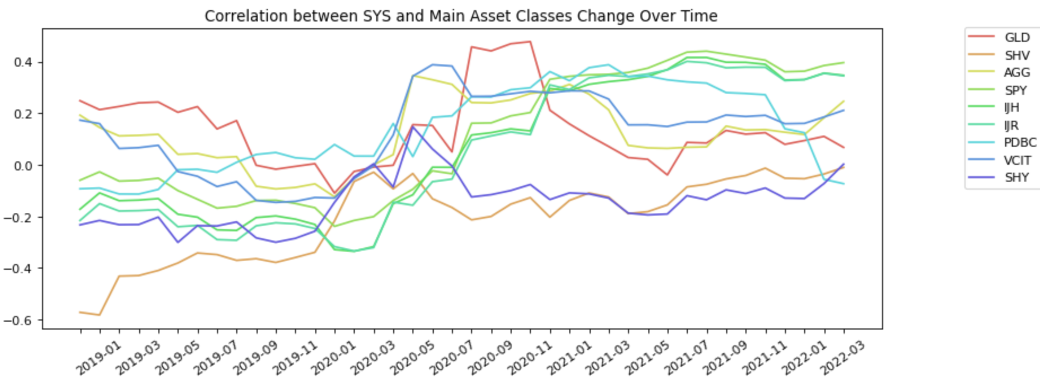
A.1. 11 Correlation between Nem versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Nem versus the other 9 ETF assets changing over time. Each correlation coefficient between Nem and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



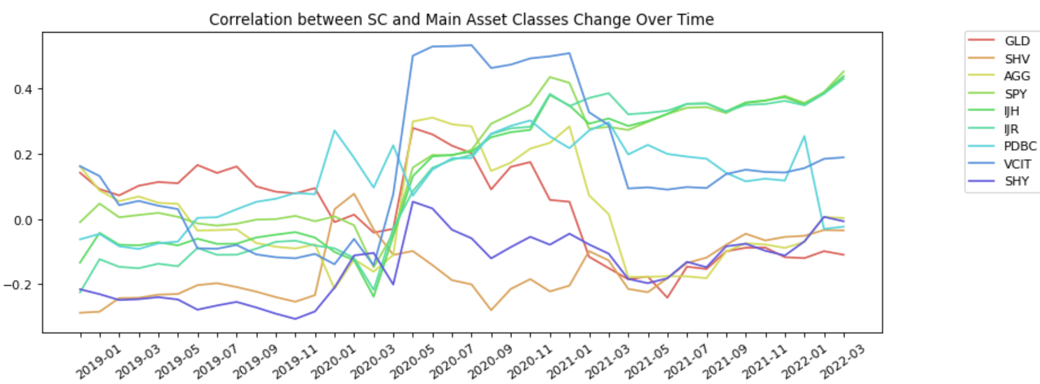
A.1. 12 Correlation between Decred versus Other ETF Assets Over Time

This figure presents the correlation coefficient lines between Decred versus the other 9 ETF assets changing over time. Each correlation coefficient between Decred and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



A.1. 13 Correlation between Syscoin versus Other ETF Assets Over Time

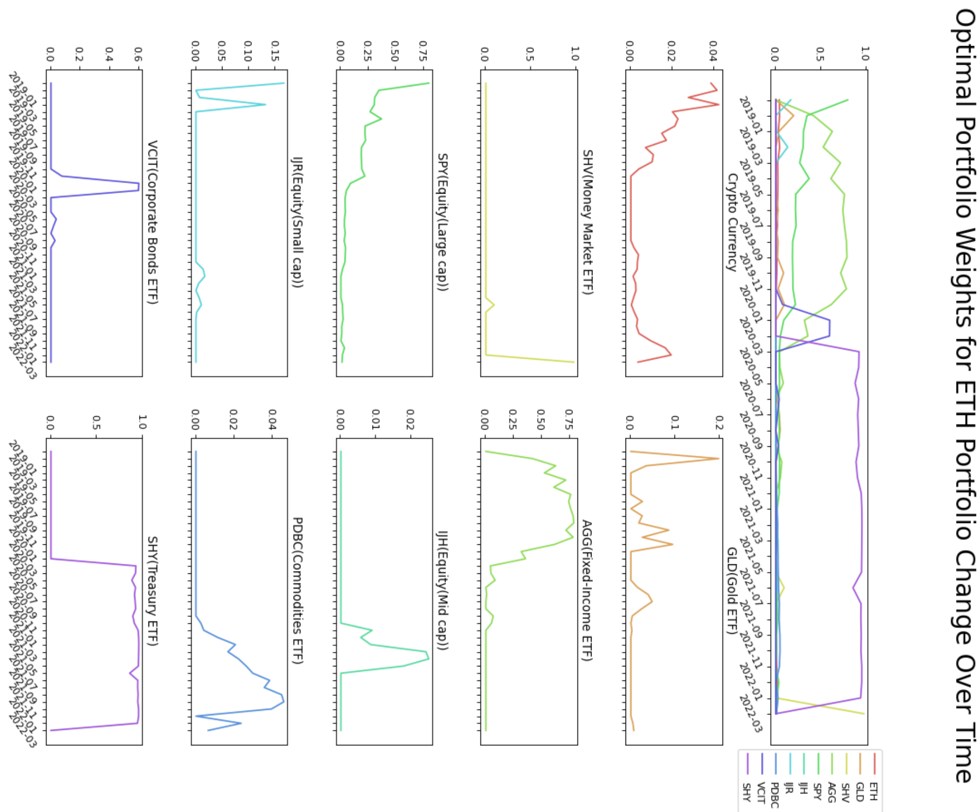
This figure presents the correlation coefficient lines between Syscoin versus the other 9 ETF assets changing over time. Each correlation coefficient between Syscoin and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.



A.1. 14 Correlation between Siacoin versus Other ETF Assets Over Time

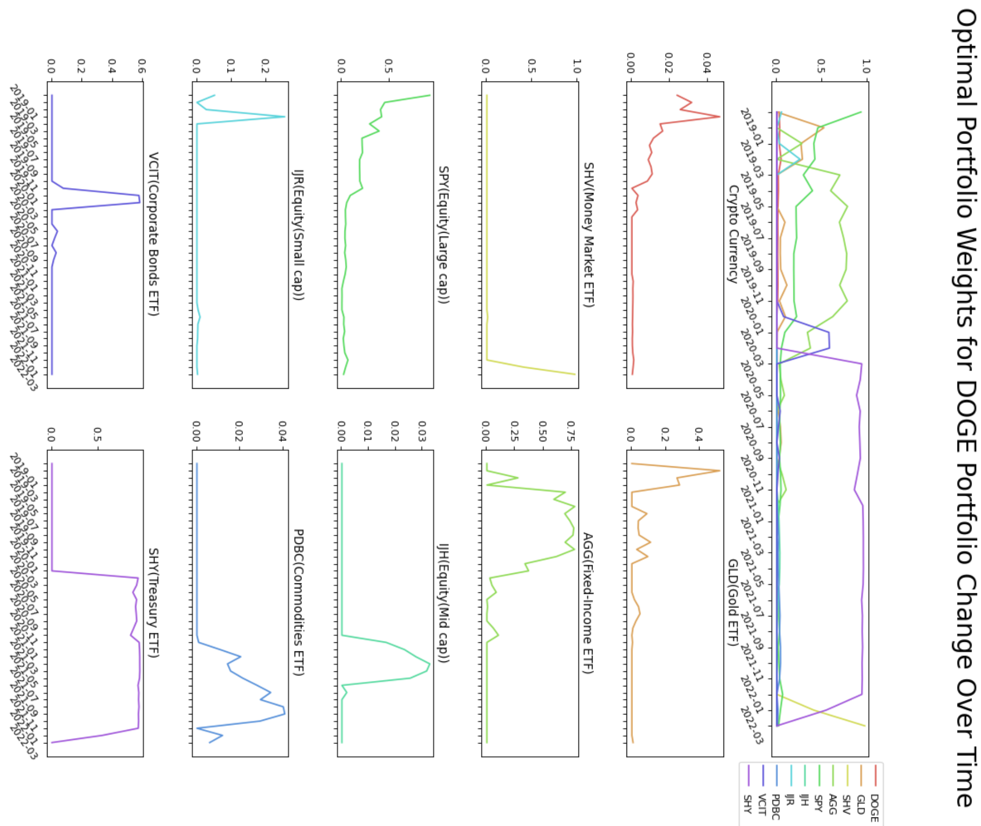
This figure presents the correlation coefficient lines between Siacoin versus the other 9 ETF assets changing over time. Each correlation coefficient between Siacoin and any ETF fund at any point in time is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the correlation coefficient results is from 2018.11 to 2022.03.

A.2 Optimal Portfolio Weights for Bitcoin Portfolio Change Over Time



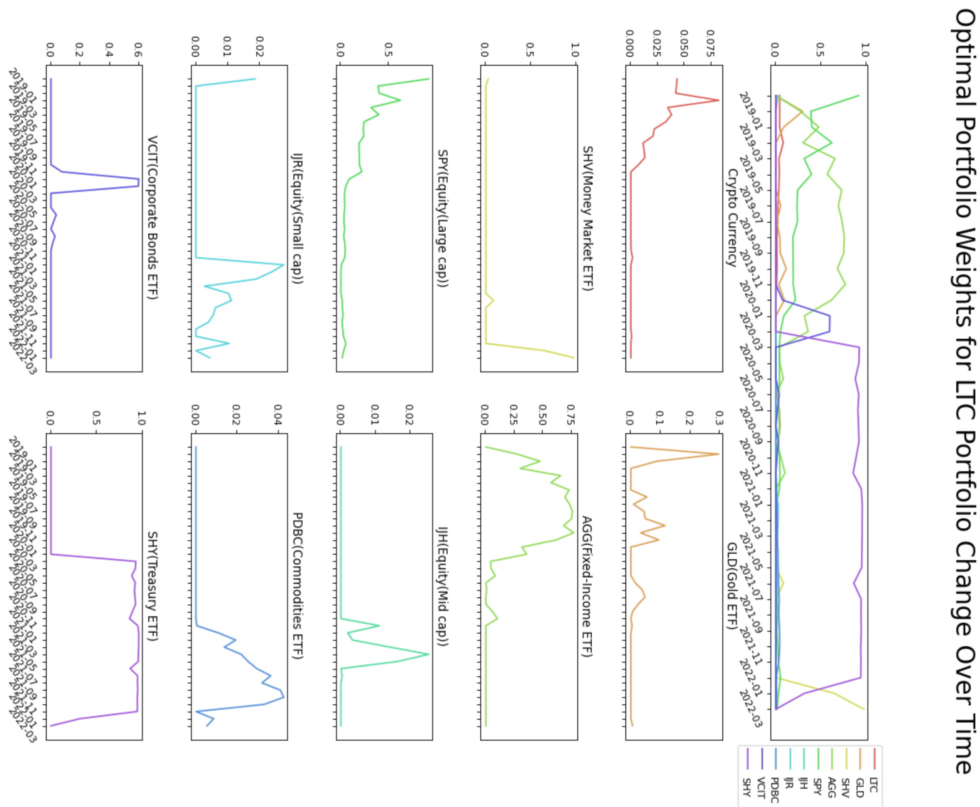
A.2. 2 Optimal Portfolio Weights for Ethereum Portfolio Change Over Time

This figure presents the optimal weight lines for Ethereum and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



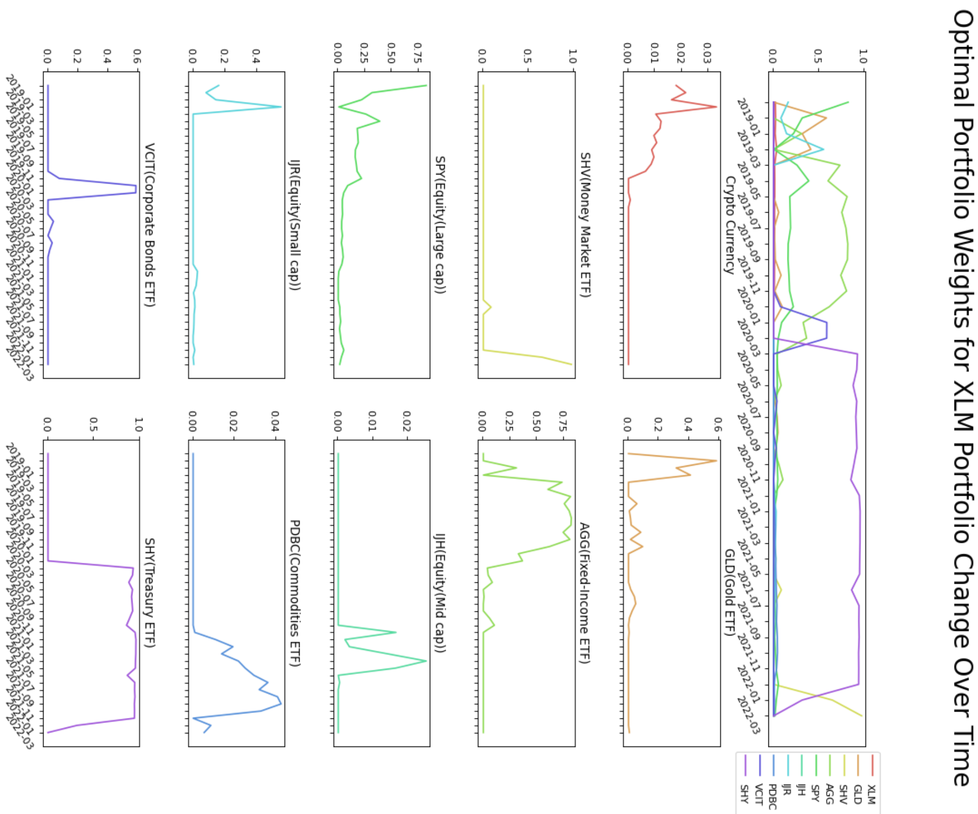
A.2. 2 Optimal Portfolio Weights for Dogecoin Portfolio Change Over Time

This figure presents the optimal weight lines for Dogecoin and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



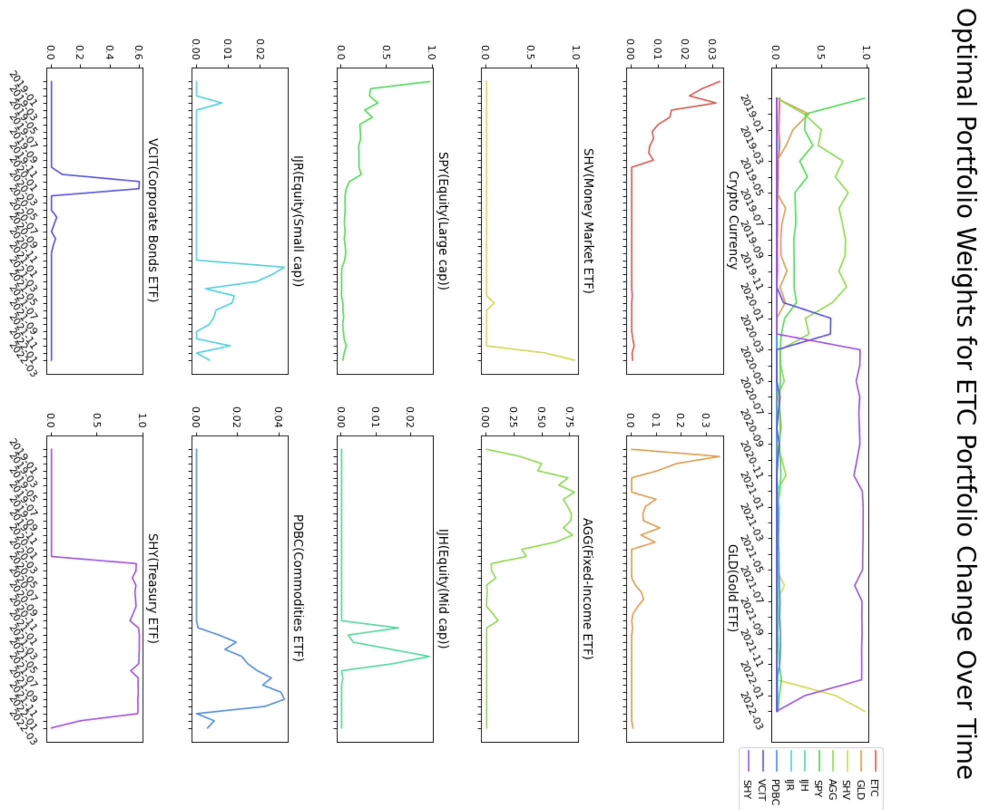
A.2. 3 Optimal Portfolio Weights for Litecoin Portfolio Change Over Time

This figure presents the optimal weight lines for Litecoin and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



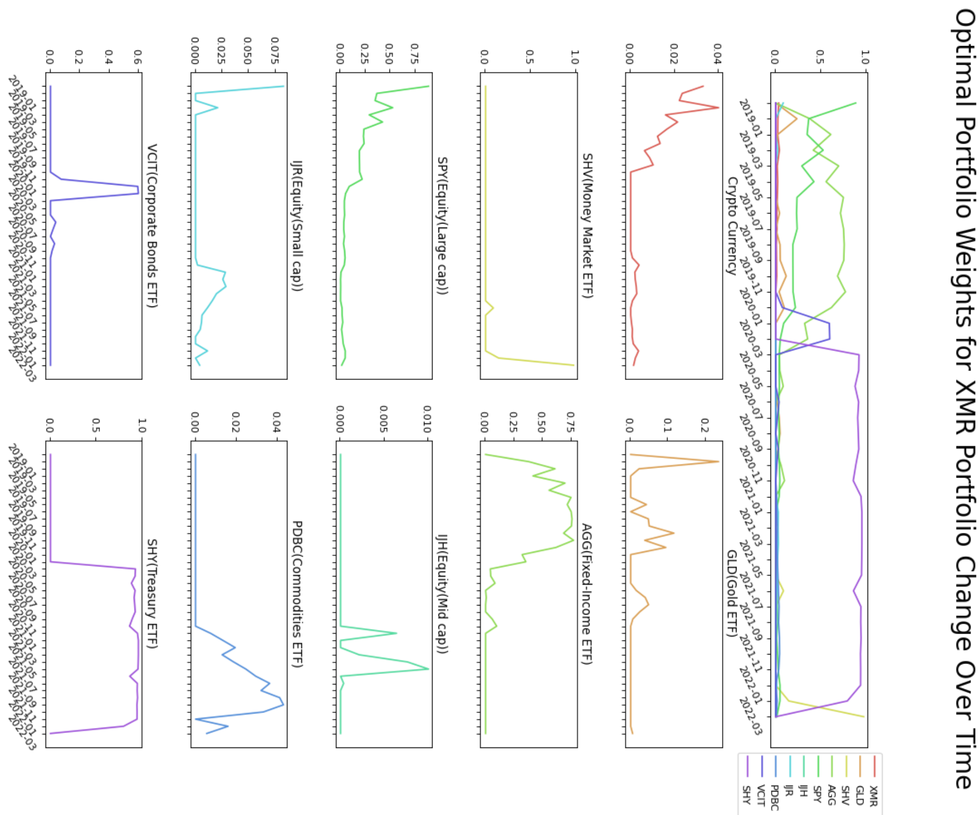
A.2. 4 Optimal Portfolio Weights for Stellar Portfolio Change Over Time

This figure presents the optimal weight lines for Stellar and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



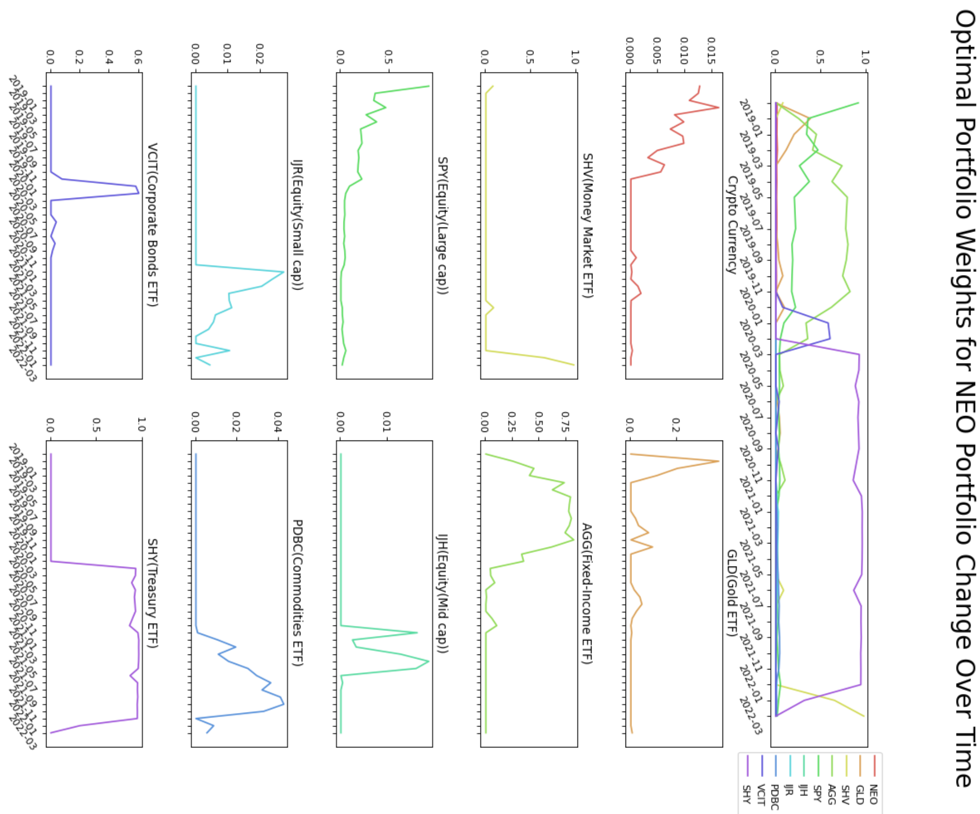
A.2. 5 Optimal Portfolio Weights for Ethereum-Classic Portfolio Change Over Time

This figure presents the optimal weight lines for Ethereum-Classic and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



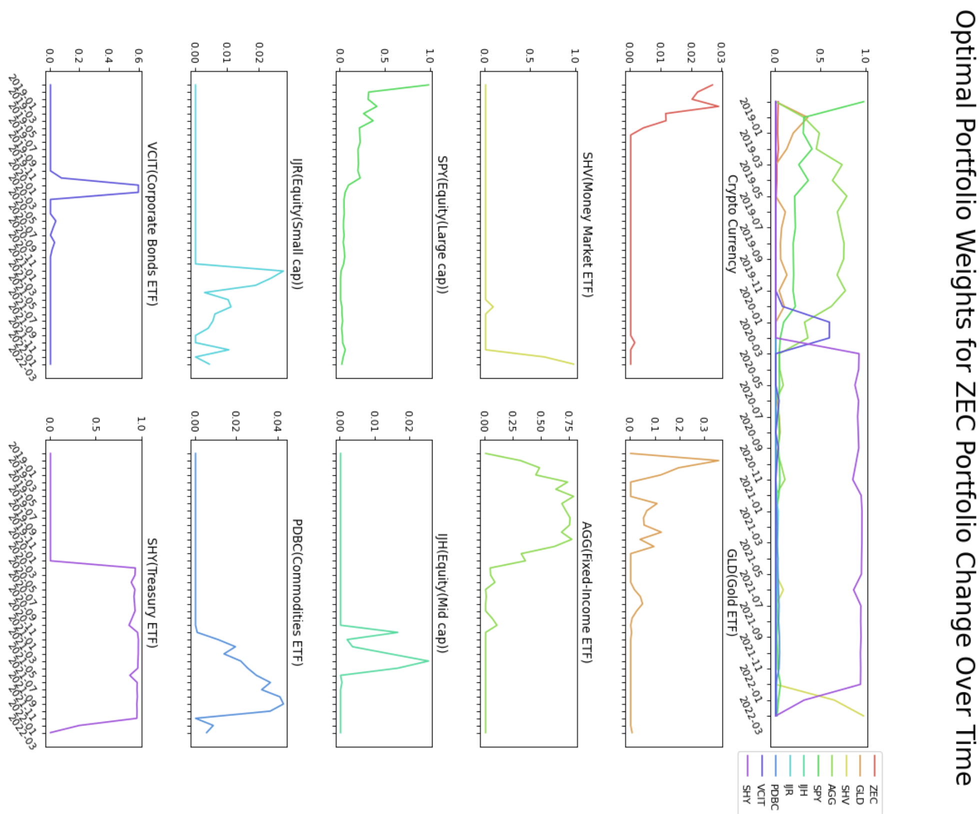
A.2. 6 Optimal Portfolio Weights for Monero Portfolio Change Over Time

This figure presents the optimal weight lines for Monero and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



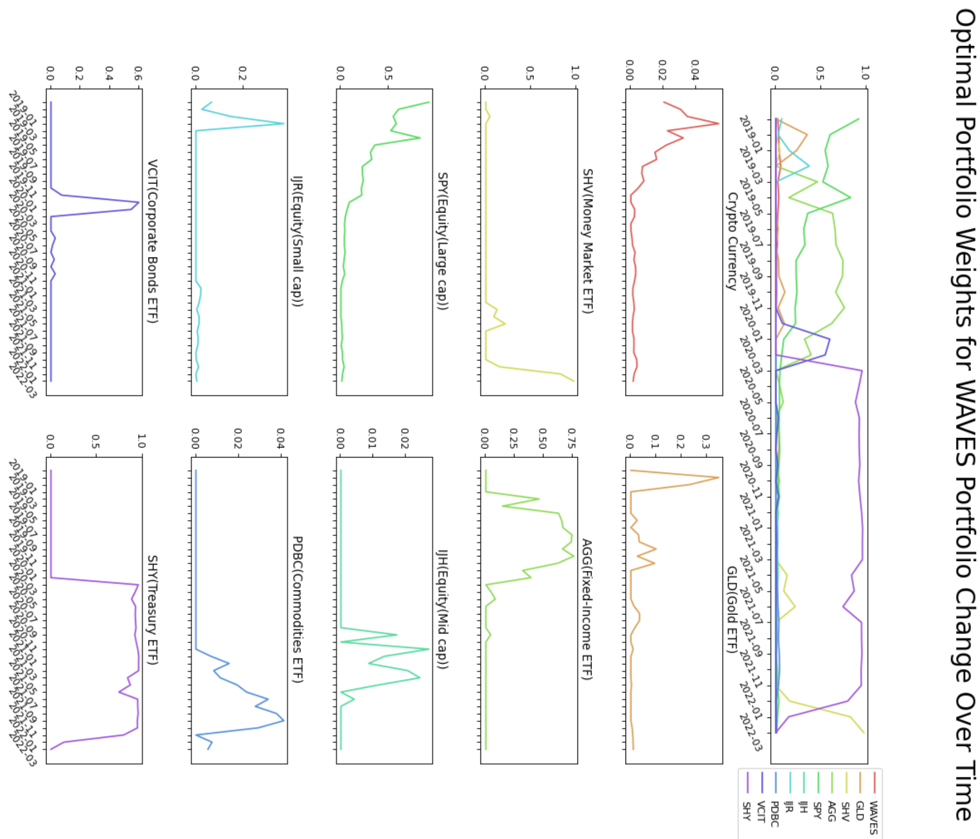
A.2. 7 Optimal Portfolio Weights for Neo Portfolio Change Over Time

This figure presents the optimal weight lines for Neo and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



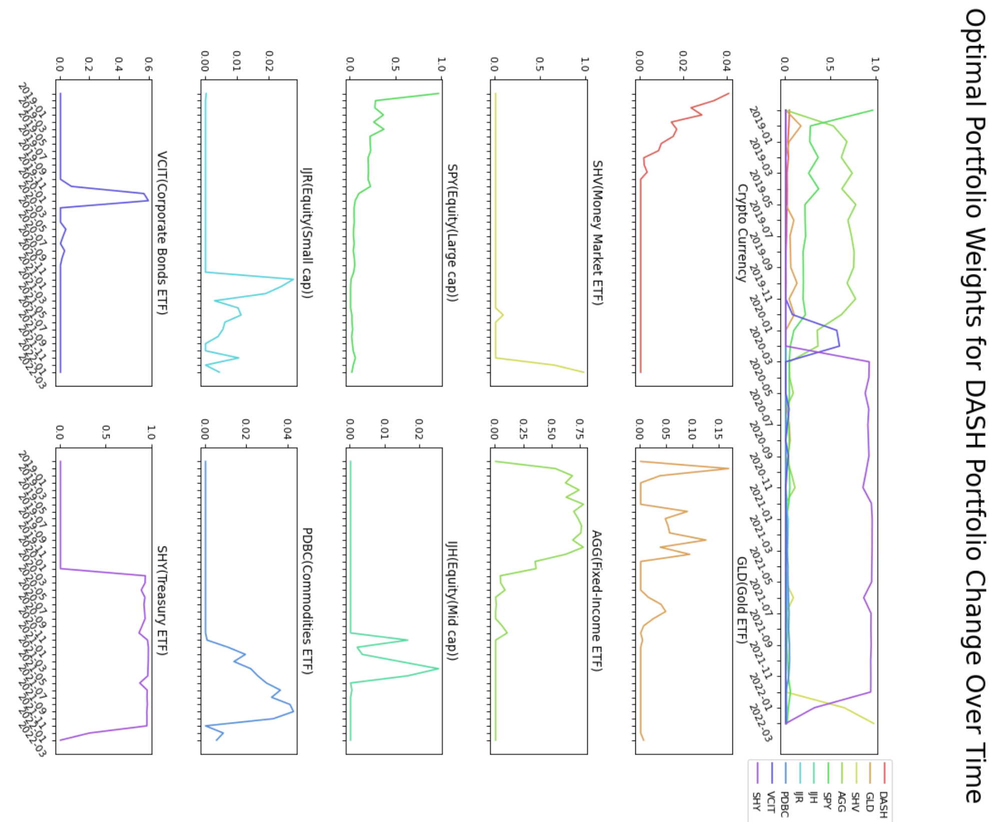
A.2. 8 Optimal Portfolio Weights for Zcash Portfolio Change Over Time

This figure presents the optimal weight lines for Zcash and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



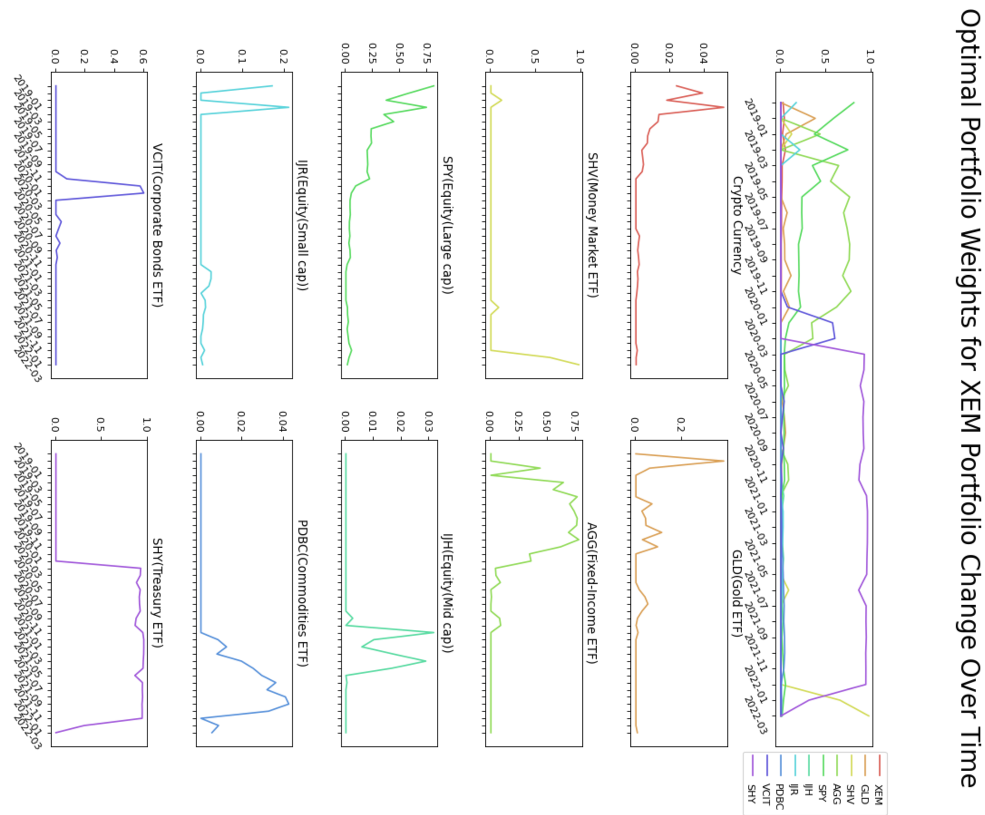
A.2. 9 Optimal Portfolio Weights for Waves Portfolio Change Over Time

This figure presents the optimal weight lines for Waves and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



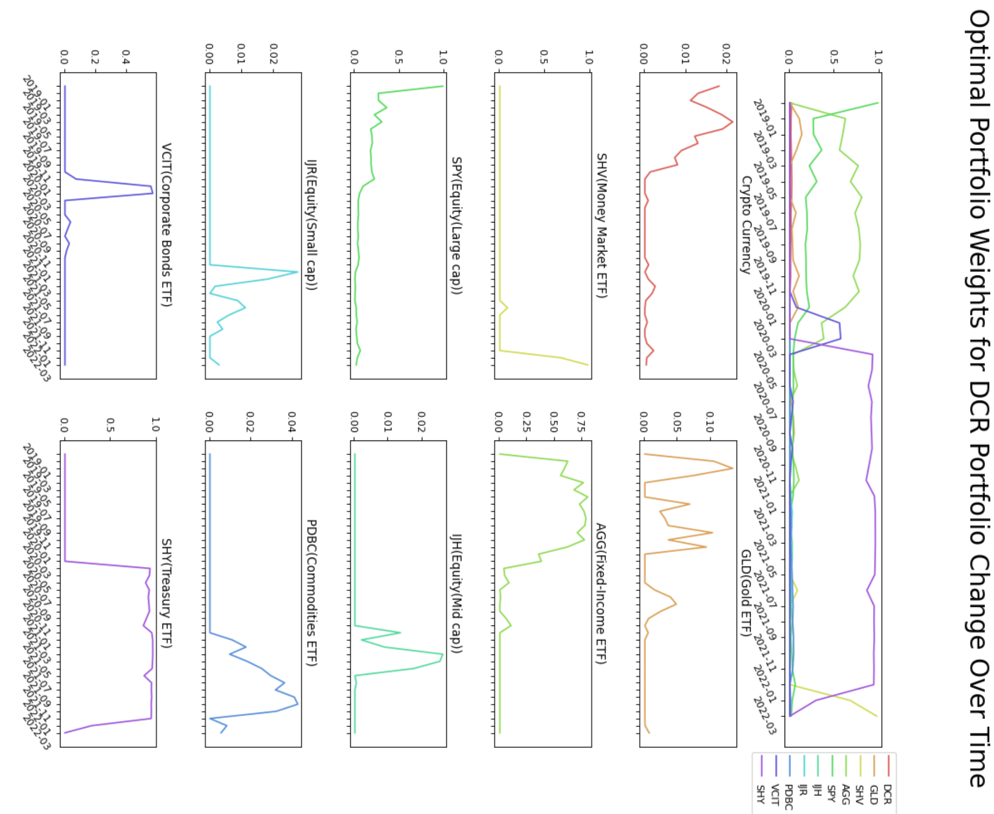
A.2. 30 Optimal Portfolio Weights for Dash Portfolio Change Over Time

This figure presents the optimal weight lines for Dash and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



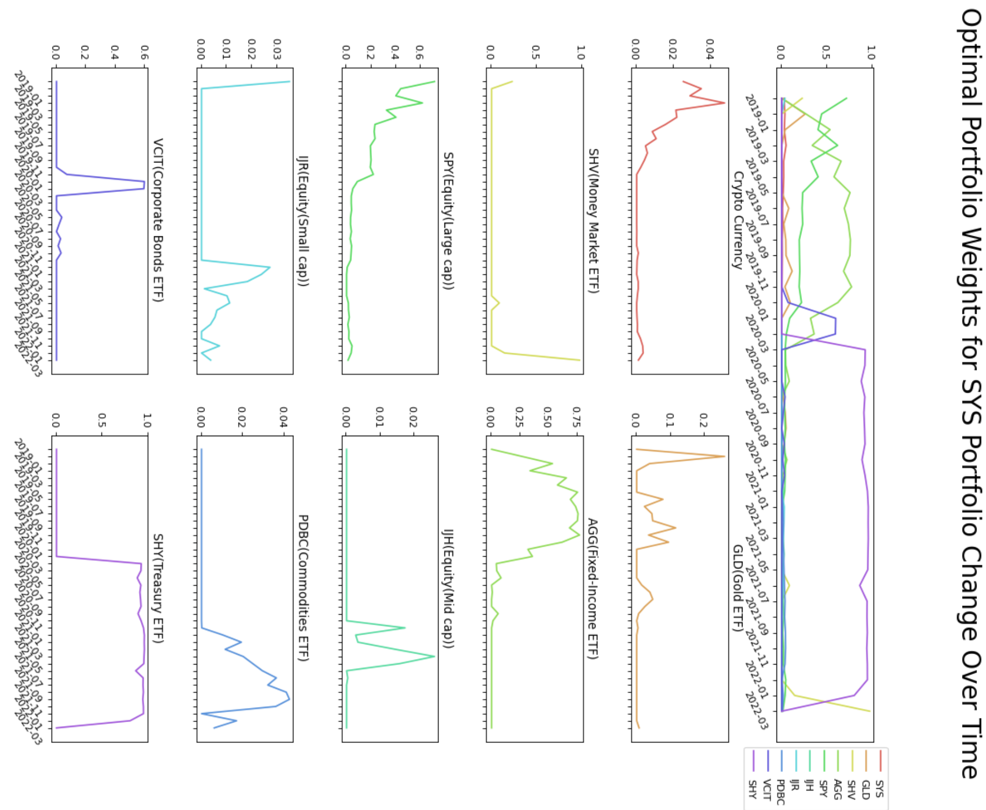
A.2. 41 Optimal Portfolio Weights for Nem Portfolio Change Over Time

This figure presents the optimal weight lines for Nem and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



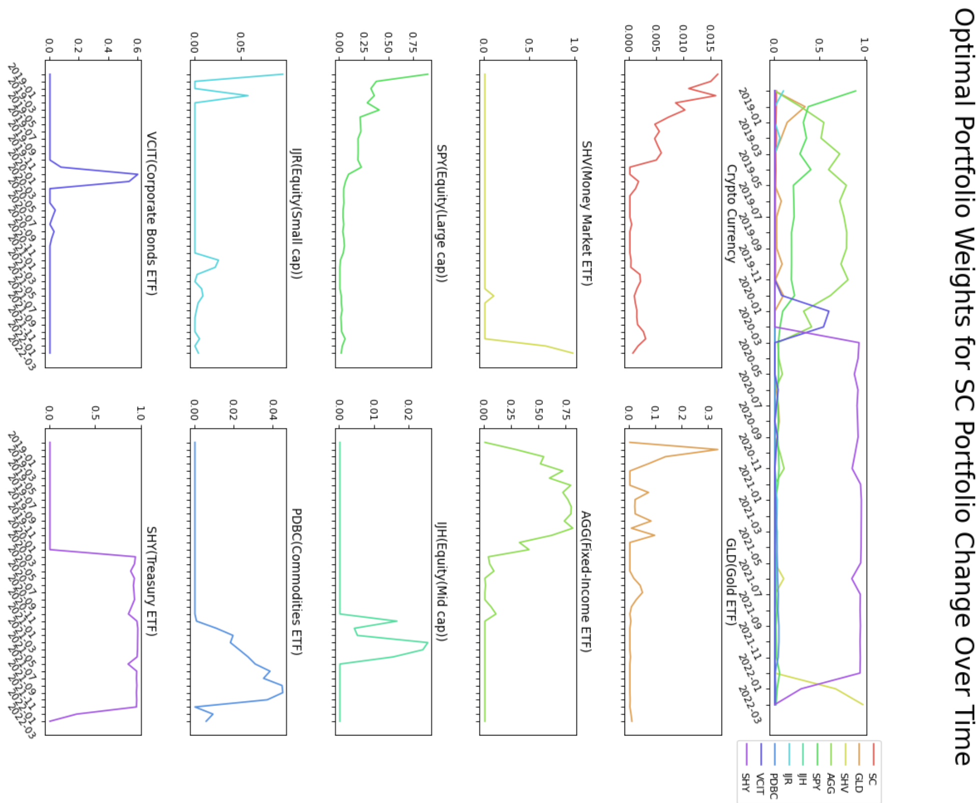
A.2. 52 Optimal Portfolio Weights for Decred Portfolio Change Over Time

This figure presents the optimal weight lines for Decred and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



A.2. 63 Optimal Portfolio Weights for Syscoin Portfolio Change Over Time

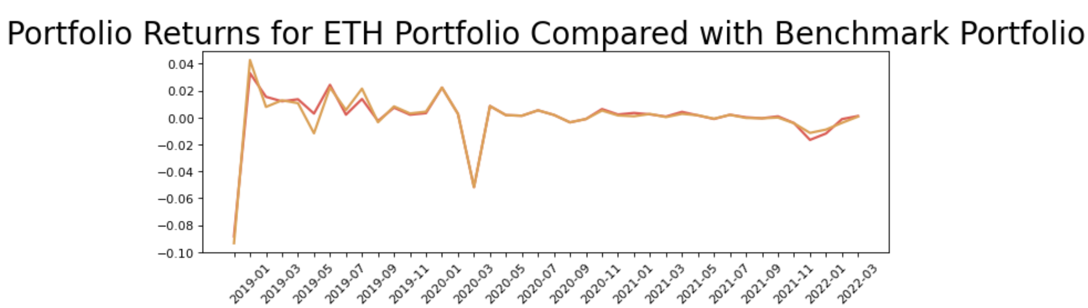
This figure presents the optimal weight lines for Syscoin and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.



A.2. 74 Optimal Portfolio Weights for Siacoin Portfolio Change Over Time

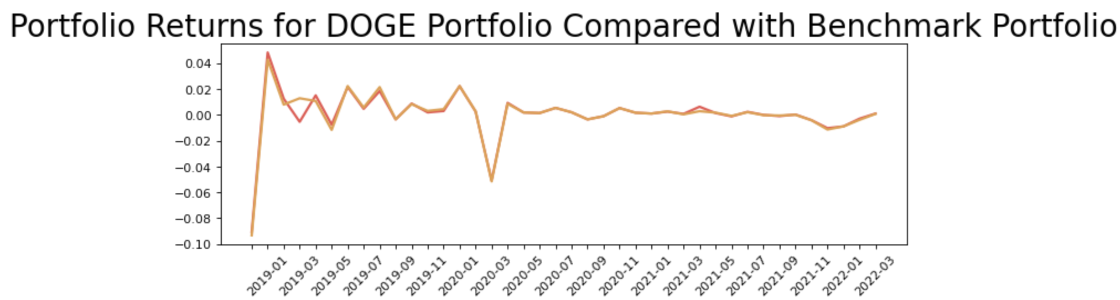
This figure presents the optimal weight lines for Siacoin and the other 9 ETFs, as well as the whole portfolio together changing over time. Each optimal weight line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for these results is from 2018.11 to 2022.03.

A.3 Portfolio Returns for BTC Portfolio Compared with Benchmark Portfolio



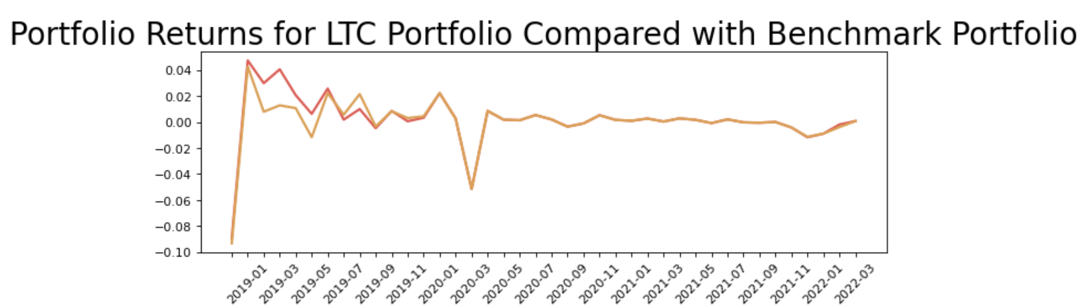
A.3. 8 Portfolio Returns for Ethereum Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Ethereum portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Ethereum portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



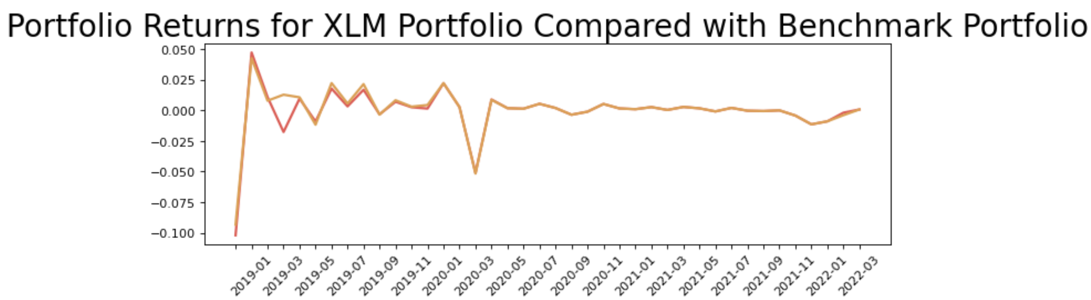
A.3. 2 Portfolio Returns for Dogecoin Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Dogecoin portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Dogecoin portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



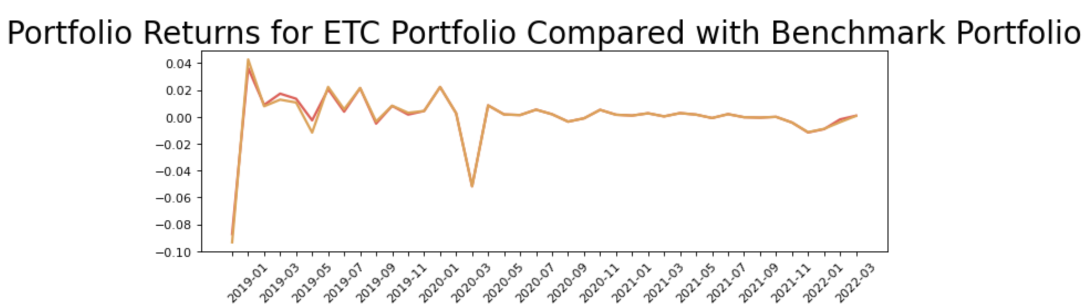
A.3. 3 Portfolio Returns for Litecoin Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Litecoin portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Litecoin portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



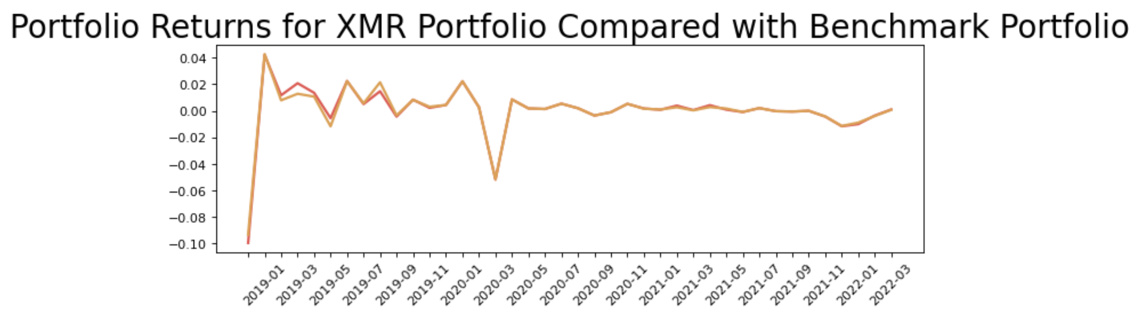
A.3. 4 Portfolio Returns for Stellar Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Stellar portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Stellar portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



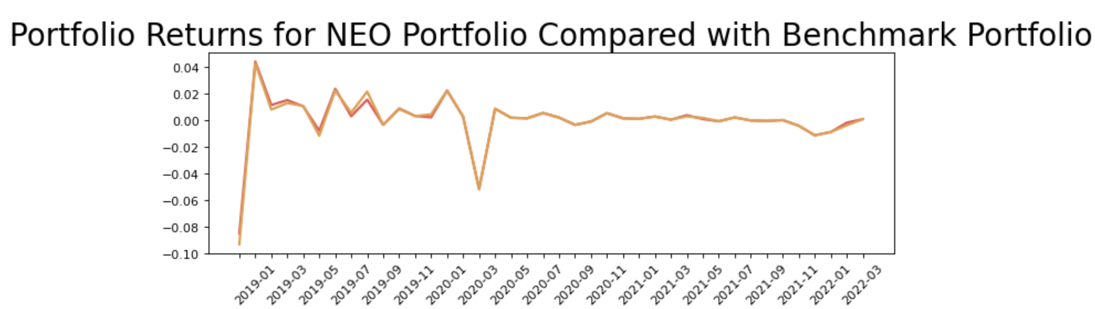
A.3. 5 Portfolio Returns for Ethereum-Classic Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Ethereum-Classic portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Ethereum-Classic portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



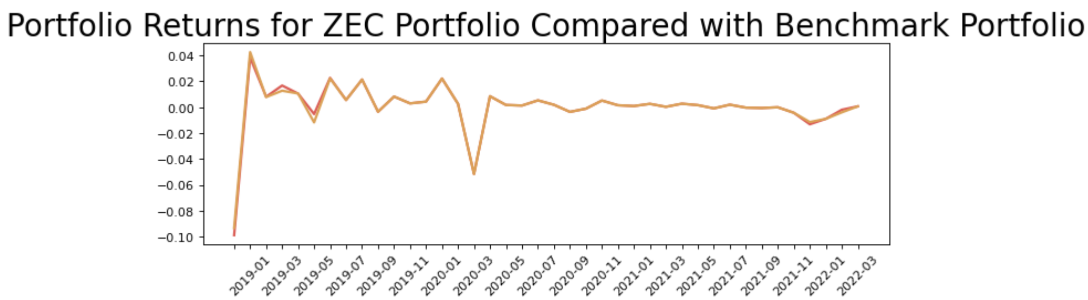
A.3. 6 Portfolio Returns for Monero Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Monero portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Monero portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



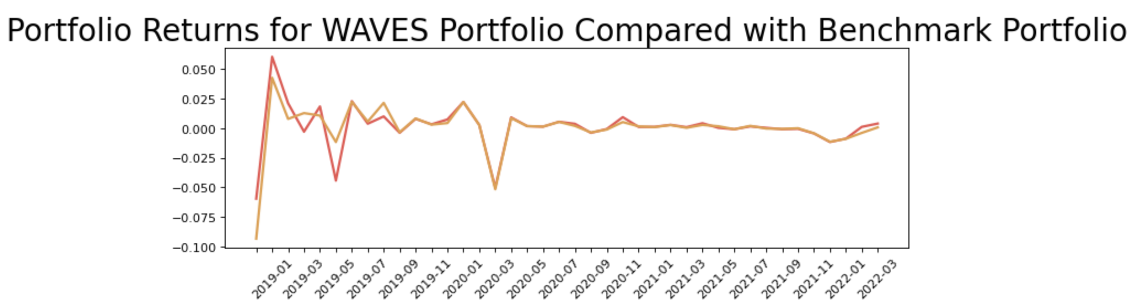
A.3. 7 Portfolio Returns for Neo Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Neo portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Neo portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



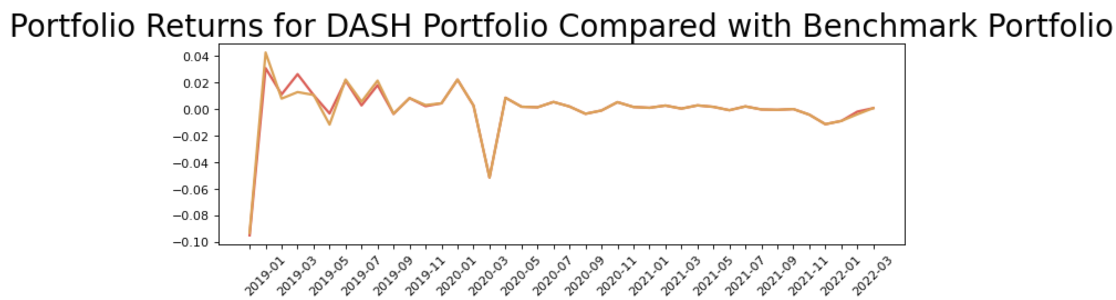
A.3. 8 Portfolio Returns for Zcash Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Zcash portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Zcash portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



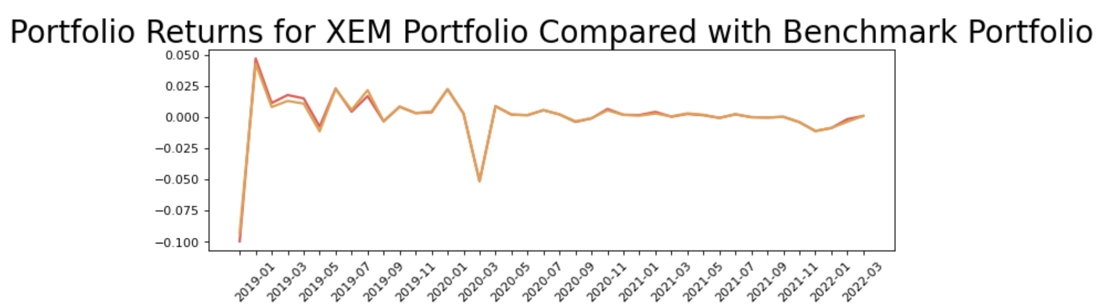
A.3. 9 Portfolio Returns for Waves Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Waves portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Waves portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



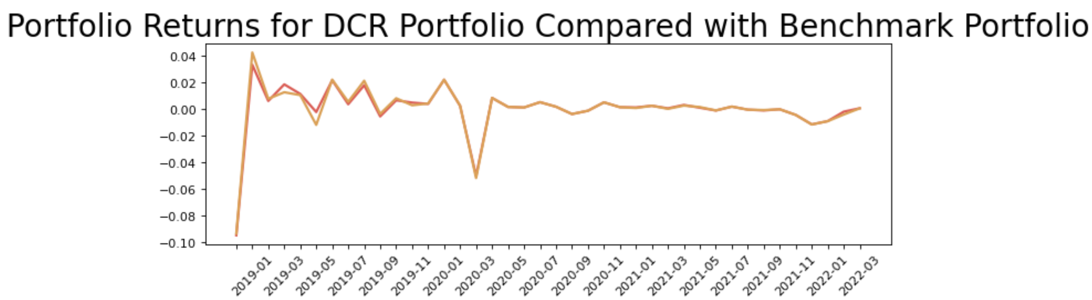
A.3. 90 Portfolio Returns for Dash Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Dash portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Dash portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



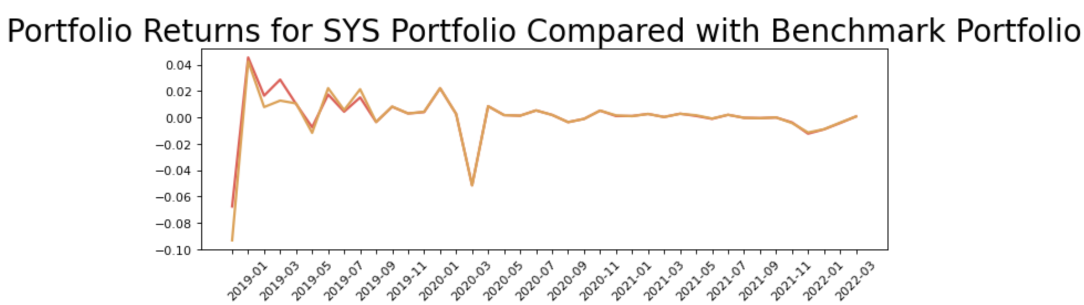
A.3. 101 Portfolio Returns for Nem Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Nem portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Nem portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



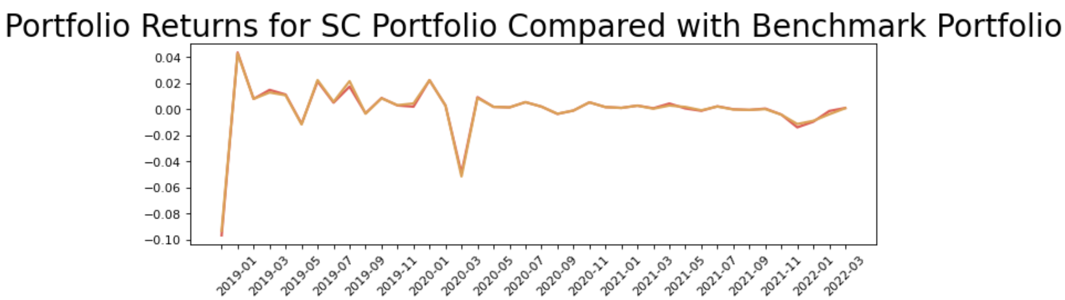
A.3. 112 Portfolio Returns for Decred Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Decred portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Decred portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



A.3. 123 Portfolio Returns for Syscoin Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Syscoin portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Syscoin portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.



A.3. 134 Portfolio Returns for Siacoin Portfolio Compared with Benchmark Portfolio

This figure presents the comparison of out-of-sample portfolio returns for the benchmark portfolio and the Siacoin portfolio changing over time. The orange line represents for the benchmark portfolio and the red line represents for the Siacoin portfolio. Each optimal portfolio return line is calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

Tables

A.4 Correlation Coefficient Results for 13 Cryptocurrencies

A.4. 14 Correlation Coefficient Results for Dogecoin

This table presents the correlation coefficient matrix of a Dogecoin portfolio consisting of Dogecoin and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Dogecoin data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	DOGE	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
DOGE	1.00									
GLD	-0.02	1.00								
SHV	-0.09	0.14	1.00							
AGG	0.03	0.38	0.37	1.00						
SPY	0.08	0.14	-0.06	0.08	1.00					
IJH	0.09	0.08	-0.13	0.02	0.93	1.00				
IJR	0.11	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	0.04	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.05	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.03	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 2 Correlation Coefficient Results for Litecoin

This table presents the correlation coefficient matrix of a Litecoin portfolio consisting of Litecoin and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Litecoin data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	LTC	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
LTC	1.00									
GLD	0.08	1.00								
SHV	-0.18	0.14	1.00							
AGG	0.15	0.38	0.37	1.00						
SPY	0.17	0.14	-0.06	0.08	1.00					
IJH	0.16	0.08	-0.13	0.02	0.93	1.00				
IJR	0.13	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.03	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.18	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.04	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 3 Correlation Coefficient Results for Stellar

This table presents the correlation coefficient matrix of a Stellar portfolio consisting of Stellar and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Stellar data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	XLM	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
XLM	1.00									
GLD	-0.05	1.00								
SHV	-0.10	0.14	1.00							
AGG	0.08	0.38	0.37	1.00						
SPY	0.14	0.14	-0.06	0.08	1.00					
IJH	0.10	0.08	-0.13	0.02	0.93	1.00				
IJR	0.07	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.02	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.10	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	

SHY	-0.09	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 4 Correlation Coefficient Results for Ethereum-Classic

This table presents the correlation coefficient matrix of an Ethereum-Classic portfolio consisting of Ethereum-Classic and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Ethereum-Classic data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	ETC	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
ETC	1.00									
GLD	0.13	1.00								
SHV	-0.10	0.14	1.00							
AGG	0.10	0.38	0.37	1.00						
SPY	0.14	0.14	-0.06	0.08	1.00					
IJH	0.10	0.08	-0.13	0.02	0.93	1.00				
IJR	0.06	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.02	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.14	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.05	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 5 Correlation Coefficient Results for Monero

This table presents the correlation coefficient matrix of a Monero portfolio consisting of Monero and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Monero data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	XMR	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY

XMR	1.00									
GLD	0.13	1.00								
SHV	-0.12	0.14	1.00							
AGG	0.10	0.38	0.37	1.00						
SPY	0.11	0.14	-0.06	0.08	1.00					
IJH	0.08	0.08	-0.13	0.02	0.93	1.00				
IJR	0.01	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.07	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.11	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.05	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 6 Correlation Coefficient Results for Neo

This table presents the correlation coefficient matrix of a Neo portfolio consisting of Neo and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Neo data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	NEO	**GLD**	**SHV**	**AGG**	**SPY**	**IJH**	**IJR**	**PDBC**	**VCIT**	**SHY**
NEO	1.00									
GLD	-0.02	1.00								
SHV	-0.05	0.14	1.00							
AGG	0.01	0.38	0.37	1.00						
SPY	0.06	0.14	-0.06	0.08	1.00					
IJH	0.05	0.08	-0.13	0.02	0.93	1.00				
IJR	0.05	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.00	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.04	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.07	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 7 Correlation Coefficient Results for Zcash

This table presents the correlation coefficient matrix of a Zcash portfolio consisting of Zcash and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Zcash data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	ZEC	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
ZEC	1.00									
GLD	0.09	1.00								
SHV	-0.05	0.14	1.00							
AGG	0.11	0.38	0.37	1.00						
SPY	0.23	0.14	-0.06	0.08	1.00					
IJH	0.17	0.08	-0.13	0.02	0.93	1.00				
IJR	0.12	-0.02	-0.15	-0.03	0.86	0.97	1.00			
DBC	-0.05	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.18	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.08	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 8 Correlation Coefficient Results for Waves

This table presents the correlation coefficient matrix of a Waves portfolio consisting of Waves and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Waves data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	WAVES	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
WAVES	1.00									
GLD	0.02	1.00								

SHV	-0.28	0.14	1.00							
AGG	-0.05	0.38	0.37	1.00						
SPY	0.04	0.14	-0.06	0.08	1.00					
IJH	-0.02	0.08	-0.13	0.02	0.93	1.00				
IJR	-0.05	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	0.01	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	-0.04	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.22	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 9 Correlation Coefficient Results for Dash

This table presents the correlation coefficient matrix of a Dash portfolio consisting of Dash and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Dash data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	DASH	**GLD**	**SHV**	**AGG**	**SPY**	**IJH**	**IJR**	**PDBC**	**VCIT**	**SHY**
DASH	1.00									
GLD	0.05	1.00								
SHV	-0.00	0.14	1.00							
AGG	0.13	0.38	0.37	1.00						
SPY	0.18	0.14	-0.06	0.08	1.00					
IJH	0.14	0.08	-0.13	0.02	0.93	1.00				
IJR	0.09	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.04	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.14	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	0.01	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 150 Correlation Coefficient Results for Nem

This table presents the correlation coefficient matrix of a Nem portfolio consisting of Nem and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Nem data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	XEM	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
XEM	1.00									
GLD	-0.00	1.00								
SHV	-0.18	0.14	1.00							
AGG	0.08	0.38	0.37	1.00						
SPY	0.10	0.14	-0.06	0.08	1.00					
IJH	0.06	0.08	-0.13	0.02	0.93	1.00				
IJR	0.02	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.00	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.08	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.03	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 161 Correlation Coefficient Results for Decred

This table presents the correlation coefficient matrix of a Decred portfolio consisting of Decred and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Decred data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	DCR	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
DCR	1.00									
GLD	0.02	1.00								

SHV	-0.08	0.14	1.00							
AGG	-0.01	0.38	0.37	1.00						
SPY	0.11	0.14	-0.06	0.08	1.00					
IJH	0.13	0.08	-0.13	0.02	0.93	1.00				
IJR	0.11	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	0.06	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.04	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.03	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 172 Correlation Coefficient Results for Syscoin

This table presents the correlation coefficient matrix of a Syscoin portfolio consisting of Syscoin and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Syscoin data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	SYS	**GLD**	**SHV**	**AGG**	**SPY**	**IJH**	**IJR**	**PDBC**	**VCIT**	**SHY**
SYS	1.00									
GLD	0.06	1.00								
SHV	-0.24	0.14	1.00							
AGG	0.11	0.38	0.37	1.00						
SPY	0.17	0.14	-0.06	0.08	1.00					
IJH	0.13	0.08	-0.13	0.02	0.93	1.00				
IJR	0.11	-0.02	-0.15	-0.03	0.86	0.97	1.00			
PDBC	-0.06	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00		
VCIT	0.11	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	
SHY	-0.08	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.4. 183 Correlation Coefficient Results for Siacoin

This table presents the correlation coefficient matrix of a Siacoin portfolio consisting of Siacoin and 9 ETFs. The ETF data are taken from both the ETF Database and the CRSP dataset from the Wharton Research Data Services (WRDS), and the Siacoin data is taken from Coinmarketcap.com, the sample period is from 2016.12 to 2022.03. All data are changed into monthly returns and the correlation coefficient values are rounded to 2 decimals.

	SC	GLD	SHV	AGG	SPY	IJH	IJR	PDBC	VCIT	SHY
SC	1.00	-0.02	-0.13	0.02	0.09	0.06	0.02	-0.04	0.05	-0.09
GLD	-0.02	1.00	0.14	0.38	0.14	0.08	-0.02	-0.08	0.36	0.23
SHV	-0.13	0.14	1.00	0.37	-0.06	-0.13	-0.15	-0.22	0.14	0.64
AGG	0.02	0.38	0.37	1.00	0.08	0.02	-0.03	-0.28	0.77	0.73
SPY	0.09	0.14	-0.06	0.08	1.00	0.93	0.86	0.11	0.49	-0.27
IJH	0.06	0.08	-0.13	0.02	0.93	1.00	0.97	0.13	0.49	-0.31
IJR	0.02	-0.02	-0.15	-0.03	0.86	0.97	1.00	0.16	0.44	-0.33
PDBC	-0.04	-0.08	-0.22	-0.28	0.11	0.13	0.16	1.00	0.01	-0.39
VCIT	0.05	0.36	0.14	0.77	0.49	0.49	0.44	0.01	1.00	0.29
SHY	-0.09	0.23	0.64	0.73	-0.27	-0.31	-0.33	-0.39	0.29	1.00

A.5 Descriptive Statistics of Bitcoin Portfolio (Different Levels)

A.5. 19 Descriptive Statistics of Ethereum Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Ethereum portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Ethereum returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Ethereum's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Ethereum itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-3.04	12.97	0.04%
Historical	40	0.04%	1.90%	-8.83%	-0.07%	0.21%	0.56%	3.29%	12.12%	-2.82	13.76	0.04%
Level 5%	40	0.05%	1.95%	-9.24%	-0.09%	0.16%	0.53%	4.23%	13.47%	-2.74	14.00	0.04%
Level 10%	40	0.12%	1.91%	-9.03%	-0.09%	0.12%	0.70%	4.05%	13.08%	-2.51	12.44	0.04%
Level 15%	40	0.17%	1.92%	-8.81%	-0.07%	0.19%	0.71%	3.89%	12.70%	-2.21	10.00	0.04%
Level 20%	40	0.15%	2.02%	-8.81%	-0.19%	0.17%	0.92%	4.35%	13.16%	0.41	-0.39	7.67%
ETH itself	40	12.17%	28.04%	-39.23%	-13.19%	8.51%	29.64%	78.23%	117.46%	1.60	1.80	0.01%
Weights of ETH	40	0.89%	1.19%	0.00%	0.02%	0.32%	1.53%	4.22%	4.22%	0.59	-1.52	0.00%

A.5. 2 Descriptive Statistics of Dogecoin Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Dogecoin portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Dogecoin returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Dogecoin's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Dogecoin itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.54	12.16	0.04%
Historical	40	0.02%	1.99%	-9.08%	-0.17%	0.14%	0.52%	4.82%	13.90%	-2.77	12.99	0.04%
Level 5%	40	0.04%	1.99%	-9.30%	-0.09%	0.18%	0.65%	4.30%	13.60%	-1.75	9.63	0.05%
Level 10%	40	0.22%	2.19%	-9.23%	-0.10%	0.17%	0.86%	5.74%	14.97%	0.73	10.69	0.07%
Level 15%	40	0.40%	2.72%	-9.16%	-0.11%	0.16%	0.97%	11.68%	20.84%	2.72	17.22	0.12%
Level 20%	40	0.60%	3.45%	-9.08%	-0.14%	0.16%	1.14%	17.77%	26.86%	4.27	18.02	183.57%
DOGE itself	40	32.99%	137.21%	-26.65%	-12.77%	-1.10%	22.88%	694.41%	721.06%	2.32	5.84	0.01%
Weights of DOGE	40	0.61%	1.03%	0.00%	0.02%	0.05%	0.95%	4.64%	4.64%	0.59	-1.52	0.00%

A.5. 3 Descriptive Statistics of Litecoin Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Litecoin portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Litecoin returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Litecoin's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Litecoin itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.04	9.47	0.04%
Historical	40	0.19%	2.12%	-8.98%	-0.07%	0.17%	0.56%	4.73%	13.70%	-2.39	11.48	0.04%
Level 5%	40	0.08%	2.06%	-9.27%	-0.09%	0.14%	0.52%	4.40%	13.67%	-1.70	10.81	0.04%

Level 10%	40	0.20%	2.12%	-9.22%	-0.07%	0.10%	0.73%	5.73%	14.95%	-0.89	8.89	0.05%
Level 15%	40	0.29%	2.29%	-9.18%	-0.08%	0.07%	0.79%	7.33%	16.51%	-0.10	6.52	0.06%
Level 20%	40	0.36%	2.53%	-8.77%	-0.20%	0.08%	0.92%	8.84%	17.61%	0.37	-0.66	6.88%
LTC itself	40	6.63%	26.55%	-34.45%	-13.33%	4.39%	23.01%	64.20%	98.64%	2.16	5.04	0.03%
Weights of LTC	40	1.01%	1.83%	0.00%	0.00%	0.00%	1.25%	8.18%	8.18%	0.59	-1.52	0.00%

A.5. 4 Descriptive Statistics of Stellar Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Stellar portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Stellar returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Stellar's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Stellar itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**	**range**	**skewness**	**kurtosis**	**variance**
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.93	14.27	0.04%
Historical	40	-0.10%	2.11%	-10.21%	-0.13%	0.15%	0.37%	4.72%	14.93%	-2.79	13.56	0.04%
Level 5%	40	0.05%	1.98%	-9.33%	-0.09%	0.16%	0.57%	4.26%	13.60%	-2.71	13.45	0.04%
Level 10%	40	0.08%	1.99%	-9.35%	-0.09%	0.14%	0.77%	4.27%	13.63%	-2.59	12.90	0.04%
Level 15%	40	0.11%	2.02%	-9.39%	-0.11%	0.12%	0.76%	4.29%	13.67%	-2.52	13.00	0.04%
Level 20%	40	0.16%	2.02%	-9.42%	-0.13%	0.11%	0.74%	4.30%	13.72%	2.26	6.14	16.42%
XLM itself	40	6.55%	41.04%	-36.48%	-22.23%	-1.92%	20.93%	160.18%	196.66%	1.99	4.34	0.01%

Weights of XLM	40	0.44%	0.76%	0.00%	0.00%	0.00%	0.89%	3.31%	3.31%	0.59	-1.52	0.00%

A.5. 5 Descriptive Statistics of Ethereum-Classic Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Ethereum-Classic portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Ethereum-Classic returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Ethereum-Classic's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Ethereum-Classic itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**	**range**	**skewness**	**kurtosis**	**variance**	
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.89	12.55	0.04%
Historical	40	0.04%	1.90%	-8.72%	-0.10%	0.16%	0.52%	3.62%	12.34%	-1.41	9.79	0.05%
Level 5%	40	0.13%	2.24%	-9.24%	-0.09%	0.14%	0.60%	6.89%	16.13%	0.13	10.48	0.06%
Level 10%	40	0.20%	2.50%	-9.09%	-0.12%	0.11%	0.60%	10.08%	19.16%	1.31	12.73	0.08%
Level 15%	40	0.26%	2.80%	-8.93%	-0.13%	0.14%	0.64%	12.78%	21.71%	2.20	15.36	0.10%
Level 20%	40	0.32%	3.17%	-8.74%	-0.15%	0.16%	0.78%	15.61%	24.35%	1.96	4.55	18.18%
ETC itself	40	12.20%	43.18%	-34.45%	-18.00%	5.52%	27.94%	158.30%	192.76%	2.08	3.58	0.01%
Weights of ETC	40	0.47%	0.89%	0.00%	0.00%	0.00%	0.69%	3.25%	3.25%	0.59	-1.52	0.00%

A.5. 6 Descriptive Statistics of Monero Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Monero portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Monero returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Monero's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Monero itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-3.06	14.23	0.04%
Historical	40	0.03%	2.08%	-9.95%	-0.10%	0.17%	0.52%	4.21%	14.16%	-2.18	11.43	0.04%
Level 5%	40	0.08%	2.11%	-9.44%	-0.12%	0.15%	0.53%	5.02%	14.46%	-1.31	11.26	0.05%
Level 10%	40	0.18%	2.22%	-9.52%	-0.15%	0.10%	0.64%	7.18%	16.70%	-0.52	10.17	0.06%
Level 15%	40	0.21%	2.46%	-9.69%	-0.12%	0.10%	0.86%	9.05%	18.74%	-0.06	9.88	0.07%
Level 20%	40	0.24%	2.71%	-9.98%	-0.12%	0.16%	1.04%	10.60%	20.58%	0.78	0.62	6.03%
XMR itself	40	6.01%	24.88%	-35.59%	-11.96%	4.25%	16.10%	71.40%	106.99%	1.94	3.38	0.01%
Weights of XMR	40	0.62%	0.98%	0.00%	0.00%	0.12%	0.90%	4.00%	4.00%	0.59	-1.52	0.00%

A.5. 7 Descriptive Statistics of Neo Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Neo portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Neo returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Neo's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Neo itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.55	11.49	0.04%
Historical	40	0.04%	1.91%	-8.53%	-0.10%	0.15%	0.52%	4.40%	12.93%	-2.88	14.37	0.04%
Level 5%	40	0.05%	1.94%	-9.32%	-0.10%	0.16%	0.54%	4.26%	13.58%	-2.98	16.31	0.03%
Level 10%	40	0.10%	1.89%	-9.31%	-0.12%	0.12%	0.59%	4.29%	13.60%	-2.77	14.54	0.04%
Level 15%	40	0.11%	1.94%	-9.31%	-0.11%	0.12%	0.68%	4.30%	13.60%	-2.63	12.92	0.04%
Level 20%	40	0.12%	2.00%	-9.30%	-0.24%	0.10%	0.88%	4.31%	13.61%	0.51	-0.15	9.72%
NEO itself	40	7.61%	31.58%	-42.32%	-17.53%	4.90%	26.48%	91.01%	133.33%	1.35	0.61	0.00%
Weights of NEO	40	0.30%	0.46%	0.00%	0.00%	0.00%	0.57%	1.63%	1.63%	0.59	-1.52	0.00%

A.5. 8 Descriptive Statistics of Zcash Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Zcash portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Zcash returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Zcash's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Zcash itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from

Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-3.17	14.61	0.04%
Historical	40	0.02%	2.05%	-9.89%	-0.09%	0.17%	0.54%	3.84%	13.73%	-1.89	10.88	0.05%
Level 5%	40	0.06%	2.21%	-9.64%	-0.13%	0.13%	0.52%	6.10%	15.75%	-0.44	11.17	0.06%
Level 10%	40	0.11%	2.49%	-9.94%	-0.21%	0.12%	0.49%	9.39%	19.34%	0.72	13.13	0.08%
Level 15%	40	0.13%	2.81%	-10.39%	-0.29%	0.11%	0.53%	12.24%	22.63%	1.64	14.97	0.10%
Level 20%	40	0.14%	3.14%	-10.58%	-0.41%	0.09%	0.36%	14.76%	25.34%	1.24	2.77	13.19%
ZEC itself	40	7.43%	36.78%	-36.97%	-20.36%	1.67%	32.67%	140.83%	177.80%	2.46	4.92	0.01%
Weights of ZEC	40	0.31%	0.77%	0.00%	0.00%	0.00%	0.00%	2.88%	2.88%	0.59	-1.52	0.00%

A.5. 9 Descriptive Statistics of Waves Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Waves portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Waves returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Waves' expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Waves itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-0.79	5.21	0.04%
Historical	40	0.09%	1.91%	-5.96%	-0.08%	0.14%	0.59%	6.04%	12.00%	-2.45	11.62	0.04%
Level 5%	40	0.04%	1.89%	-8.53%	-0.09%	0.15%	0.79%	4.69%	13.22%	-1.85	9.77	0.03%
Level 10%	40	0.08%	1.86%	-7.88%	-0.10%	0.12%	0.84%	5.29%	13.17%	-1.23	7.88	0.03%
Level 15%	40	0.13%	1.85%	-7.25%	-0.07%	0.15%	0.82%	5.78%	13.03%	-0.84	6.29	0.03%
Level 20%	40	0.15%	1.84%	-6.63%	-0.09%	0.13%	0.78%	5.85%	12.48%	1.91	3.91	34.76%
WAVES itself	40	20.48%	59.71%	-40.16%	-19.08%	2.96%	35.77%	236.71%	276.87%	2.19	4.82	0.01%
Weights of WAVES	40	0.79%	1.21%	0.00%	0.13%	0.22%	0.73%	5.40%	5.40%	0.59	-1.52	0.00%

A.5. 200 Descriptive Statistics of Dash Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Dash portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Dash returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Dash's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Dash itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-3.22	14.40	0.04%
Historical	40	0.02%	1.99%	-9.52%	-0.09%	0.17%	0.52%	3.09%	12.61%	-0.81	9.74	0.05%
Level 5%	40	0.15%	2.36%	-9.35%	-0.10%	0.14%	0.52%	8.24%	17.59%	1.64	14.37	0.09%

Level 10%	40	0.27%	2.96%	-9.40%	-0.19%	0.11%	0.52%	13.97%	23.37%	3.30	20.92	0.13%
Level 15%	40	0.39%	3.71%	-9.45%	-0.18%	0.13%	0.56%	19.83%	29.28%	4.32	26.16	0.20%
Level 20%	40	0.52%	4.57%	-9.50%	-0.34%	0.13%	0.78%	25.92%	35.42%	2.48	8.86	15.73%
DASH itself	40	6.22%	40.16%	-38.03%	-23.65%	-1.87%	21.35%	182.62%	220.65%	2.27	4.51	0.01%
Weights of DASH	40	0.49%	1.02%	0.00%	0.00%	0.00%	0.20%	4.06%	4.06%	0.59	-1.52	0.00%

A.5. 211 Descriptive Statistics of Nem Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Nem portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Nem returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Nem's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Nem itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.91	13.89	0.04%
Historical	40	0.04%	2.12%	-10.01%	-0.10%	0.17%	0.56%	4.69%	14.70%	-2.75	12.83	0.04%
Level 5%	40	0.05%	2.01%	-9.35%	-0.10%	0.17%	0.61%	4.27%	13.61%	-2.60	12.38	0.04%
Level 10%	40	0.10%	2.04%	-9.36%	-0.10%	0.16%	0.82%	4.30%	13.66%	-2.35	10.74	0.04%
Level 15%	40	0.14%	2.14%	-9.38%	-0.11%	0.18%	0.89%	4.41%	13.79%	-2.05	9.64	0.05%
Level 20%	40	0.20%	2.21%	-9.39%	-0.10%	0.19%	0.97%	4.84%	14.23%	2.20	5.41	20.67%
XEM itself	40	8.02%	46.04%	-44.65%	-17.38%	0.70%	12.23%	169.80%	214.44%	3.07	9.96	0.01%

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Weights of XEM	40	0.52%	1.07%	0.00%	0.00%	0.09%	0.41%	5.10%	5.10%	0.59	-1.52	0.00%

A.5. 222 Descriptive Statistics of Decred Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Decred portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Decred returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Decred's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Decred itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**	**range**	**skewness**	**kurtosis**	**variance**
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-3.27	14.89	0.04%
Historical	40	0.01%	1.96%	-9.47%	-0.10%	0.16%	0.52%	3.34%	12.81%	-2.90	14.14	0.04%
Level 5%	40	0.03%	1.96%	-9.35%	-0.09%	0.16%	0.60%	4.26%	13.61%	-2.96	14.76	0.04%
Level 10%	40	0.08%	1.94%	-9.37%	-0.07%	0.18%	0.68%	4.15%	13.51%	-2.89	14.25	0.04%
Level 15%	40	0.15%	1.97%	-9.38%	-0.09%	0.18%	0.72%	4.02%	13.40%	-2.81	13.48	0.04%
Level 20%	40	0.18%	2.00%	-9.40%	-0.13%	0.19%	0.97%	3.90%	13.30%	1.48	2.78	9.53%
DCR itself	40	6.71%	31.26%	-39.59%	-12.58%	5.05%	14.55%	100.80%	140.39%	1.32	0.32	0.00%
Weights of DCR	40	0.44%	0.67%	0.00%	0.00%	0.05%	0.81%	2.13%	2.13%	0.59	-1.52	0.00%

A.5. 233 Descriptive Statistics of Syscoin Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Syscoin portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Syscoin returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Syscoin's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Syscoin itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-1.72	7.63	0.03%
Historical	40	0.12%	1.76%	-6.76%	-0.11%	0.15%	0.52%	4.55%	11.31%	-2.74	13.68	0.04%
Level 5%	40	0.09%	1.93%	-9.12%	-0.09%	0.16%	0.59%	4.30%	13.42%	-2.52	13.38	0.04%
Level 10%	40	0.15%	1.92%	-8.97%	-0.15%	0.16%	0.65%	4.36%	13.33%	-2.12	11.20	0.04%
Level 15%	40	0.19%	1.98%	-8.82%	-0.17%	0.14%	0.75%	4.41%	13.23%	-1.72	9.25	0.04%
Level 20%	40	0.21%	2.07%	-8.74%	-0.19%	0.10%	0.78%	4.70%	13.44%	1.83	3.97	33.78%
SYS itself	40	18.15%	58.86%	-52.19%	-17.71%	2.08%	32.42%	230.34%	282.52%	2.23	4.67	0.01%
Weights of SYS	40	0.61%	1.12%	0.00%	0.00%	0.06%	0.50%	4.74%	4.74%	0.59	-1.52	0.00%

A.5. 244 Descriptive Statistics of Siacoin Portfolio (Different Levels)

This table presents the descriptive statistics of the benchmark portfolio as well as the Siacoin portfolio according to the total count, the means, standard deviations, minimum, 25% percentile, median, 75% percentile, maximum values, ranges, skewness, and the kurtosis of excess returns for each sector. The second row shows the results calculated using real historical Siacoin returns, while rows three to six show the descriptive statistics for the most available portfolio returns with Siacoin's expected return set at 5%, 10%, 15%, and 20% respectively. The last two rows show the results in data form for the descriptive statistics of Siacoin itself and the descriptive statistics of the optimal weights obtained from its historical data, respectively. The cryptocurrency data are taken from Coinmarketcap.com, the ETF data are taken from both the ETF Database and the CRSP dataset of the Wharton Research Data Services (WRDS). All data are calculated based on the rolling window approach, where every estimation window is 24 months. The time horizon for the result is from 2018.11 to 2022.03.

	count	mean	std	min	25%	50%	75%	max	range	skewness	kurtosis	variance
Benchmark	40	0.01%	2.01%	-9.33%	-0.09%	0.17%	0.54%	4.26%	13.60%	-2.96	13.98	0.04%
Historical	40	0.00%	2.03%	-9.68%	-0.12%	0.16%	0.52%	4.34%	14.02%	-2.96	15.17	0.04%
Level 5%	40	0.07%	1.92%	-9.34%	-0.10%	0.17%	0.62%	4.27%	13.61%	-3.01	16.03	0.04%
Level 10%	40	0.11%	1.90%	-9.34%	-0.12%	0.21%	0.62%	4.29%	13.63%	-2.97	15.71	0.04%
Level 15%	40	0.14%	1.92%	-9.35%	-0.13%	0.23%	0.83%	4.32%	13.66%	-2.87	14.63	0.04%
Level 20%	40	0.17%	1.95%	-9.35%	-0.14%	0.26%	0.86%	4.34%	13.69%	1.72	4.57	19.22%
SC itself	40	10.76%	44.40%	-56.26%	-18.58%	4.26%	27.82%	173.48%	229.74%	1.68	2.06	0.00%
Weights of SC	40	0.34%	0.45%	0.00%	0.01%	0.14%	0.49%	1.62%	1.62%	0.59	-1.52	0.00%