HEC MONTRÉAL

# The Peer Performance Ratios in Cryptocurrency Markets

**par**

**Abhishek Duggal**

**David Ardia**
**HEC Montréal**
**Directeur de recherche**

**Sciences de la gestion**
**(Spécialisation M.Sc. Financial Engineering)**

*Mémoire présenté en vue de l'obtention*
*du grade de maîtrise ès sciences*
*(M. Sc.)*

April 2023

# Acknowledgements

I would like to express my gratitude to my research director, David Ardia, for his support and patience throughout this thesis. His advice and feedback have helped me a lot. His support is crucial to this thesis. Without him, it would have been impossible for me to finish this thesis. I really appreciate the opportunities to work under him and thank him for his support.

Also, I would like to thank my beloved family and friends who have motivated me and supported me during my studies.

# Abstract

This thesis applies the peer performance ratio method to the cryptocurrency investment universe to develop and evaluate investment strategies. Drawing on the work of Ardia and Boudt (2018), the PPR method employs a triple-layer approach for evaluating peer performance, addressing the issue of false discoveries arising from using estimated alpha. It proposes using three ratios: Equal, Under, and Outperformance, and a closed-form non-parametric estimator to mitigate false discoveries.

The study investigates the heterogeneity of returns in the cryptocurrency market, utilizing trading data for 53 cryptocurrencies over a 5-year period from 2017 to 2022. The methodology involves analyzing the presence of return heterogeneity by employing peer performance ratios and developing screening plots based on underperformance, equal performance, and outperformance ratios. Investment strategies are then evaluated based on three outperformance metrics: Alpha (average returns), Sharpe ratio, and Modified Sharpe ratio. Corresponding benchmark investment strategies are also implemented using these metrics. Rebalancing is conducted at daily, weekly, and monthly frequencies to assess effectiveness.

Returns statistics, drawdown statistics, and risk-adjusted performance statistics are evaluated to compare the performance of the returns. The results demonstrate that peer performance-based methods exhibit strong performance depending on the investment objectives, highlighting the PPR method's potential for navigating the unique challenges of the cryptocurrency market and generating consistent returns. This study contributes to the development and refinement of investment strategies tailored to the evolving cryptocurrency market, providing valuable insights for investors seeking to capitalize on its immense potential.

# Contents

# Chapter 1

# Introduction

The rapid expansion of the cryptocurrency market since Bitcoin's introduction in 2009 (Nakamoto, 2008) has piqued the interest of investors and researchers alike. In April 2021, the market capitalization of cryptocurrencies surpassed $1.19 trillion (CoinMarketCap, 2023), giving rise to various investment trends such as Initial Coin Offerings (ICOs), Security Token Offerings (STOs), and Initial Exchange Offerings (IEOs). However, the market's inherent volatility and unpredictability present considerable challenges for investors seeking consistent returns (Corbet et al., 2018).

Traditional financial concepts and techniques have been examined within the context of the cryptocurrency market. Still, their application is often limited by factors such as decentralization, regulatory ambiguity, and high transaction costs (Momtaz, 2020a; Bouri et al., 2017). As a result, researchers have explored alternative investment strategies specifically designed for this unique market.

In the context of this thesis, we employ the peer performance methodology introduced by Ardia and Boudt (2018), which can help to identify cryptocurrencies that outperform their peers. This innovative methodology provides investors with a quantitative framework for evaluating investment opportunities in the market. In this thesis, we implement the peer performance methodology as an investment strategy in the cryptocurrency market. We focus on a rolling window investment analysis of 5-year cryptocurrency data using the outperformance ratio method and peer performance ratios.

Previous literature has investigated various investment strategies in the cryptocurrency market, yielding mixed results. For instance, the Moving Average Crossover (MAC) strategy generated positive returns but was not statistically significant after accounting for transaction costs (Gkillas and Katsiampa, 2018). Time-varying approaches employing technical indicators demonstrated positive returns, but their efficacy varied across cryptocurrencies and time periods (Caporale et al., 2018). Likewise, momentum and contrarian strategies produced excess returns, although their profitability declined over time (Trimborn and Wolfgang KH, 2019).

Brière et al. (2015) also investigated the diversification benefits of including Bitcoin in traditional financial portfolios. They found that a small allocation to Bitcoin improved the portfolio's risk-return profile, but they also highlighted the extreme volatility and uncertain regulatory environment as potential challenges for investors.

The peer performance methodology offers a novel alternative for investors aiming to navigate the unique challenges of the cryptocurrency market and achieve consistent returns. As this market continues to grow, driven by factors such as increased institutional interest, mainstream adoption, and technological advancements (Phillip et al., 2018), the development and refinement of investment strategies tailored to the cryptocurrency market will be crucial for investors seeking to capitalize on its vast potential. This literature review aims to provide a comprehensive understanding of the peer performance methodology and its applications, setting the stage for our implementation of this innovative approach in the cryptocurrency market.

## 1.1 Past Work

### Introduction to Cryptocurrency Market and Investing

Cryptocurrencies, as a relatively new asset class, exhibit unique characteristics compared to traditional financial assets. These unique aspects can create both opportunities and challenges for investors. For example, one of the defining features of cryptocurrencies is their decentralization. Most cryptocurrencies operate on decentralized networks, eliminating the need for central authorities such as banks or governments. This aspect can increase transparency, reduce transaction costs, and faster transactions (Nakamoto, 2008). In contrast, traditional financial assets are often subject to centralized control and oversight, which can increase counterparty risk and limit market access.

The high price volatility of cryptocurrencies is another distinguishing characteristic. Cryptocurrencies are known for their substantial short-term gains or losses for investors due to factors such as market sentiment, regulatory changes, and technological advancements (Bouri et al., 2017). This volatility contrasts with traditional financial assets, which exhibit lower short-term price fluctuations.

Liquidity is another point of differentiation between cryptocurrencies and traditional assets. Although the liquidity of some cryptocurrencies like Bitcoin has improved over time, many smaller cryptocurrencies still face liquidity issues, which can impact the ease of trading and price discovery (Liu and Tsyvinski, 2018b). On the other hand, traditional financial assets, such as stocks and bonds, typically benefit from deeper and more liquid markets that facilitate trading and price discovery.

## Challenges in the Cryptocurrency Industry

The cryptocurrency industry faces several challenges that can affect the performance and adoption of cryptocurrencies as an investment option. Security breaches and cyberattacks on cryptocurrency exchanges, wallets, and networks can lead to significant losses for investors (Moore and Christin, 2013). The irreversibility of cryptocurrency transactions may exacerbate the impact of such attacks, in contrast to traditional financial systems that often have mechanisms for reversing fraudulent transactions.

Regulatory uncertainty is another challenge faced by the cryptocurrency industry. The evolving regulatory environment, characterized by varied approaches across different countries, can create challenges for investors as they navigate the complex and sometimes contradictory landscape (LaBonte and Rice, 2019). This situation contrasts with the established regulatory frameworks governing traditional financial assets and institutions.

Scalability concerns have also emerged as the growth of cryptocurrencies raises questions about their ability to handle increasing transaction volumes. Scalability issues can lead to slow transaction times and increased transaction fees, potentially limiting the widespread adoption of cryptocurrencies (Croman et al., 2016). Traditional financial systems, on the other hand, have had more time to develop infrastructure and processes to handle high transaction volumes.

Environmental impact is a significant challenge for the cryptocurrency industry, particularly for proof-of-work-based cryptocurrencies like Bitcoin. The energy-intensive nature of cryptocurrency mining has raised concerns about its environmental impact, which may influence investor sentiment and regulatory approaches towards cryptocurrencies (Mora et al., 2018; Stoll et al., 2019). In contrast, traditional financial assets typically have a lower direct environmental impact, although indirect effects through investments in environmentally harmful industries can still be significant.

Finally, market manipulation is another challenge facing the cryptocurrency industry. The relatively small market capitalization and lower liquidity of many cryptocurrencies make them susceptible to market manipulation, such as pump-and-dump schemes or insider trading, which can negatively impact investors (Griffin and Shams, 2020; Xu and Livshits, 2018). Traditional financial markets, with more comprehensive regulatory oversight and higher levels of liquidity, are less susceptible to market manipulation.

## Factor-Based Investing in Traditional Finance and Cryptocurrencies

Factor-based investing is an investment approach that seeks to select assets based on their exposure to certain factors, which are characteristics or attributes that can help explain differences in their returns over time. In traditional finance, factors such as size, value, momentum, quality, and low volatility have been identified as key drivers of returns (Fama and French, 1992; Jegadeesh and Titman, 1993; Asness et al., 2014; Ang et al., 2006). These factors have been extensively studied, leading to the development of investment strategies that target assets with specific factor exposures.

Applying factor-based investing to the cryptocurrency market involves identifying factors that can help explain the differences in returns among various cryptocurrencies. Research in this area is still emerging, and some studies have attempted to pinpoint factors that drive cryptocurrency returns, such as market capitalization (Elendner et al., 2016), liquidity, network value (Bouri et al., 2019), momentum, and market sentiment (Liu and Tsyvinski, 2018a; Blau et al., 2018).

The unique characteristics and challenges of the cryptocurrency market may affect the relevance and effectiveness of factor-based investing in this context. For instance, the decentralization of cryptocurrencies, eliminating the need for central authorities, contrasts with the centralized control and oversight of traditional financial assets (Nakamoto, 2008). This aspect can lead to differences in how factors, such as liquidity (Bouri et al., 2017) and market capitalization, influence asset returns in the two markets. Another point of differentiation is the high price volatility of cryptocurrencies, which contrasts with the relatively lower short-term price fluctuations of many traditional financial assets (Urquhart, 2016; Nadarajah and Chu, 2017). This difference in volatility may impact the way factors such as momentum and market sentiment affect the returns of cryptocurrencies compared to traditional assets.

Despite these differences, the application of factor-based investing to cryptocurrencies still needs to be explored, and further research is required to establish robust factors and strategies in this area. Investors may consider both traditional factor-based investing approaches and emerging cryptocurrency-focused strategies when developing investment strategies for this novel asset class. The choice between conventional factor-based investing and cryptocurrency-specific approaches will depend on individual preferences, investment objectives, and risk tolerance. So in this environment, using the peer performance methodology becomes quite compelling.

## Practical Considerations for Cryptocurrency Investing

Investors looking to implement a factor-based investing approach in the cryptocurrency market should consider several practical aspects. One key aspect is diversification. By diversifying across multiple cryptocurrencies, investors can help mitigate the impact of idiosyncratic risks associated with individual cryptocurrencies, such as security breaches or regulatory actions. A diversified portfolio can provide more stable returns over time. Another essential consideration is portfolio rebalancing. Regularly rebalancing the portfolio to maintain the desired factor exposures is critical for ensuring that the investment strategy remains consistent over time. Rebalancing can also help investors take advantage of price fluctuations by selling cryptocurrencies that have appreciated and buying those that have underperformed relative to their factor exposures. While some investors may attempt to time their exposure to different factors based on market conditions, empirical evidence suggests that factor timing is challenging and often leads to underperformance. A long-term, consistent approach to factor-based investing may be more effective for achieving desired investment outcomes. Finally, investors should be mindful of the costs of trading cryptocurrencies, such as transaction fees and bid-ask spreads, which can erode returns. Additionally, the tax implications of cryptocurrency investments can be complex and vary across jurisdictions. Therefore, investors must consult a tax professional to ensure compliance and optimize their tax situation.

By understanding the unique characteristics and challenges of cryptocurrencies and identifying relevant factors that can help explain differences in returns, investors can implement a systematic and transparent approach to cryptocurrency investing. Practical considerations, such as diversification, rebalancing, factor timing, and cost and tax implications, are essential for effectively executing a factor-based investment strategy in the cryptocurrency market. As the cryptocurrency ecosystem continues to evolve and mature, factor-based investing may become an increasingly valuable tool for investors seeking to navigate digital assets' complex and dynamic world.

## The Peer Performance Ratios

Peer performance ratios are financial metrics that enable the comparison of a company's financial performance to that of its peers or industry competitors. These ratios, encompassing measures such as return on assets, return on equity, and gross margin, among others, are vital for assessing a company's performance in relation to its industry, pinpointing areas of relative strength or weakness, and aiding investors and analysts in making informed decisions regarding a company's financial health and growth potential.Ardia and Boudt (2018) propose this method of peer performance ratios and apply it to the hedge fund investment universe to evaluate its effectiveness.

Ardia and Boudt (2018) highlight the issue of a fund's estimated alpha differing from its peers, stating that if the alpha of peer funds is genuinely identical, estimation error must be the driving factor. They reference a study by Barras et al. (2010) that accurately estimates the proportion of true positive alpha funds in the universe. The traditional approach to peer performance evaluation, which ranks funds based on their estimated alpha and uses percentile ranks to classify peer performance as either outperformance or underperformance, is criticized for overlooking the possibility that funds in the peer group can have the same alpha and tends to overestimate outperformance and underperformance.

An alternative Bayesian approach proposed by Ľuboš Pástor and Stambaugh (2002) suggests that a fund's peer performance corresponds to an analysis of the credible set associated with the fund's alpha posterior distribution. They recommend evaluating a fund's peer performance using three peer performance parameters and introducing a non-parametric estimator that controls for false discoveries. Estimating these parameters is a challenging task, and the authors present a solution to account for false discoveries in the multiple-hypothesis setup of testing the difference between the focal fund's alpha and all other peer funds.

The proposed method consists of a two-step estimation procedure combining pairwise and multiple testing advantages. The first step entails estimating the percentage of peer funds with equal performance using only pairwise tests of equal performance between the focal fund and a peer fund. The second step involves obtaining a sample of p-values for each potential pair, a mixture of uniformly distributed p-values (for pairs where the null hypothesis is correct), and p-values close to zero (for pairs where the null hypothesis is false). This approach accounts for estimation error and the joint hypothesis of testing equal performance with the peer funds. The method is robust to false positives under a multiple-hypothesis testing framework and can handle a large number of peer funds without requiring time series to be available for the same period for all funds.

Alpha-differential, obtained as the intercept in the linear factor model, serves as the pairwise peer performance measure. The study examines the distribution of peer performance across hedge funds and its relation to the individual performance measure of the fund. The paper reveals a strong positive dependence between alpha and the outperformance ratio ($\pi_i^+$), although the relationship is highly nonlinear. The traditional rank-based approach to estimating outperformance and underperformance percentages is deemed flawed, as it disregards the large proportion of equal performance between investment funds. In response, the authors propose a new approach, peer performance ratios, which considers the possibility of observing different estimates of a fund's individual performance while the true performance remains identical.

The research paper scrutinizes the added value of utilizing the outperformance ratio ($\pi_i^+$) in tandem with other performance measures to construct quintile portfolios of outperforming hedge funds. It compares the outperformance ratio ($\pi_i^+$) to four other performance measures: the fund's past return (capturing the "hot hands effect"), the fund's alpha, the fund's relative alpha, and the fund's peer alpha. The authors contend that the proposed peer performance ratios offer a unique assessment of peer performance, incremental to existing measures, and can be employed for ex-ante selection of funds and ex-post evaluation of their relative performance. Furthermore, they demonstrate that the methodology based on peer performance ratios accounts for the possibility of observing different estimates of the fund's individual performance while the true performance remains identical. This approach provides a more accurate and comprehensive assessment of a fund's performance in relation to its peers. The authors suggest that peer performance ratios offer valuable insights for both ex-ante selection of funds and ex-post evaluation of their relative performance, as they can capture nuances that traditional rank-based approaches might overlook. To facilitate the implementation of this method, the authors have also released an open-source statistical package called "PeerPerformance" that offers all the functionality documented in their article, which is utilized and discussed in the context of the proposed thesis.

## Previous Applications of the Peer Performance Ratios

Ardia et al. (2022) examines the extent to which investment managers can differentiate themselves regarding future performance when focusing on green or brown stocks, as environmentally-conscious investments gain more attention from institutional investors and asset managers. The researchers assert that a more heterogeneous universe in terms of underlying stock performance enables skilled managers to distinguish themselves from their peers more effectively.

The study employs the peer performance ratios approach by Ardia and Boudt (2018) and concentrates on firms in the S&P 500 index from 2014 to 2020. The researchers use firms' greenhouse gas emission intensity to create peer groups of green and brown stocks and utilize Carhart (1997) and Fama and French (2015) factor models to analyze the data. On average, approximately 20% of stocks differentiate themselves from their peers in terms of realized-alpha performance over various horizons, with significantly higher variability in the opportunity set within brown stocks. Additionally, this heterogeneity has diminished over time, particularly for green stocks, implying that it has become more challenging for investment managers to deploy their skills when allocating among low-GHG intensity stocks. The methodology is based on the definition of the triplet of peer performance ratios from the prior research paper, where the equal-performance ratio measures the percentage of stocks in a given peer group that cannot be differentiated in terms of performance.

The researchers form peer groups of brown and green stocks using firms' latest GHG emissions and calculate the p-value of the null hypothesis of equal performance over a forward-looking evaluation period between stocks and peers using a pairwise test. The distribution of the p-values is (asymptotically) a mixture of uniformly distributed p-values when the null hypothesis is true and p-values close to zero when the null hypothesis is false. This approach, following Ardia and Boudt (2018), enables the estimation of the proportions of equal performance, underperformance, and outperformance. The results are then used to analyze the heterogeneity of green and brown stocks' universes in terms of performance and investigate whether this heterogeneity has changed over time.

The research findings indicate that the unconditional performance heterogeneity is around 20% for both green and brown stocks. This percentage is consistently higher for brown stocks than for green stocks and is robust over the three evaluation horizons and the two-factor models used in the study. Moreover, the results show much higher variability in performance heterogeneity for brown stocks than for green stocks, suggesting that investment managers have found it easier to deploy their talent in brown stocks than in green stocks. The study also uncovers a negative trend in performance heterogeneity for green and brown firms, implying that it has become increasingly difficult for investment managers to differentiate themselves when investing in green stocks. The research further reveals that underperformance ratios drive the heterogeneity performance of brown stocks and that selecting outperforming green stocks has become more challenging for investment managers in recent years.

Considering the approach's demonstrated efficacy and suitability, provided the distinctive characteristics and limitations of the cryptocurrency investment landscape, this research will employ this methodology to devise and assess investment strategies in cryptocurrency markets.

# Chapter 2

# Investment Universe Analysis

The cryptocurrency dataset was procured from firstratedata.com, comprising data on 53 distinct cryptocurrencies. The dataset encompasses 1-minute frequency trading information, with historical records extending back to 2013. Each cryptocurrency's dataset includes the open, close, high, and low prices, in addition to the trading volume. It is important to note that the commencement date of trading for each currency may differ, as individual cryptocurrencies have entered the market at distinct intervals.

For the purpose of implementing rolling window analysis to evaluate returns based on multiple strategies, data from the 53 available cryptocurrencies were selected from 2017 to 2021. Missing data for dead or recently launched currencies within the chosen period was replaced with NA values. To alleviate computational inefficiency and enhance processing time while handling large volumes of data, a returns matrix $[R_m]$ with dimensions 1826x53 [Total Days in the chosen time period x Number of Cryptocurrencies] was generated to execute operations and implement strategy analysis. The closing price for the last trading day of each day was utilized to calculate returns for that specific day Akcora et al. (2018).

Let $P_{i,t}$ denote the closing price of cryptocurrency $i$ on day $t$. Then, the daily return $R_{i,t}$ for cryptocurrency $i$ on day $t$ can be calculated as follows:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}. \tag{2.1}$$

where $i = 1, 2, \ldots, 53$ represents each of the 53 cryptocurrencies, and $t = 1, 2, \ldots, T$

denotes each day in the period from 2017 to 2021. In this equation, $R_{i,t}$ is the daily return for cryptocurrency $i$ on day $t$, $P_{i,t}$ is the closing price of cryptocurrency $i$ on day $t$, and $P_{i,t-1}$ is the closing price of cryptocurrency $i$ on day $t-1$. By calculating $R_{i,t}$ for all cryptocurrencies $i$ and all days $t$, we obtain a matrix containing the returns data $[R_m]$ for the entire dataset.

The core computation associated with peer performance Ratios was conducted using the R PeerPerformance package available on CRAN, developed by Ardia, Boudt, and Bouamara Ardia et al. (2021). The analysis was carried out using the Performance Analytics package in R Peterson and Carl (2020).

## 2.1 Analysing the Cryptocurrency Market

Table 2.1 presents an overview of the currency dataset, detailing the statistical properties of each cryptocurrency, including the start and end dates, average monthly returns, the standard deviation of returns, and average monthly transaction value. These statistical properties correspond with the general understanding of the investment universe within the cryptocurrency market. For instance, Bitcoin (BTC) and Ethereum (ETH) are known to have relatively lower average returns and standard deviations compared to smaller, more volatile cryptocurrencies, such as Dogecoin (DOGE) and TRON (TRX) Liu and Tsyvinski (2018a); Momtaz (2020b). The table aids in illustrating the diversity of risk and return profiles within the cryptocurrency market, emphasizing the necessity for a tailored investment strategy like the peer performance methodology.

| Currency | Start Date | End Date | Avg. Returns [Monthly] (%) | Std. Dev. Returns [Monthly] (%) | Avg. Transaction Value [Monthly] ($10^6$) ($) |
|---|---|---|---|---|---|
| BTC | 01-04-2013 | 21-01-2022 | 11.02 | 47.41 | 15608.55 |
| ETH | 11-03-2016 | 21-01-2022 | 15.44 | 44.46 | 10363.72 |
| BTC-EUR | 01-01-2017 | 21-01-2022 | 9.39 | 25.35 | 3413.51 |
| LTC | 01-01-2017 | 21-01-2022 | 11.95 | 39.80 | 3058.62 |
| XRP | 01-02-2017 | 21-01-2022 | 31.64 | 121.48 | 2699.41 |
| ADA | 01-03-2018 | 21-01-2022 | 12.50 | 56.37 | 2121.07 |
| LINK | 01-07-2019 | 21-01-2022 | 12.57 | 39.86 | 1955.11 |
| EOS | 01-07-2017 | 21-01-2022 | 11.53 | 57.01 | 1818.54 |
| BCH | 04-12-2017 | 21-01-2022 | 2.54 | 34.17 | 1571.32 |
| UST | 01-12-2018 | 21-01-2022 | 0.00 | 1.25 | 1422.35 |
| USDT | 01-04-2017 | 21-01-2022 | 0.02 | 2.05 | 1183.07 |
| XLM | 01-03-2018 | 21-01-2022 | 6.02 | 43.33 | 1139.99 |
| BSV | 01-12-2018 | 21-01-2022 | 8.77 | 56.92 | 764.30 |
| DOGE | 01-06-2017 | 21-01-2022 | 75.53 | 346.30 | 713.19 |
| TRX | 07-10-2017 | 21-01-2022 | 49.57 | 293.45 | 706.06 |
| ETC | 01-01-2017 | 21-01-2022 | 14.18 | 51.54 | 638.04 |
| OMG | 01-08-2017 | 21-01-2022 | 24.43 | 129.50 | 412.86 |
| NEO | 07-09-2017 | 21-01-2022 | 7.24 | 40.09 | 392.10 |
| ZEC | 01-01-2017 | 21-01-2022 | 8.17 | 39.37 | 374.12 |
| XTZ | 03-07-2017 | 21-01-2022 | 12.47 | 48.26 | 364.25 |
| USDC | 08-01-2020 | 21-01-2022 | -0.08 | 0.40 | 360.83 |
| LRC | 07-04-2018 | 21-01-2022 | 19.00 | 74.39 | 336.89 |
| MANA | 01-08-2017 | 21-01-2022 | 34.95 | 116.07 | 292.49 |
| XMR | 01-01-2017 | 21-01-2022 | 10.72 | 44.25 | 251.16 |
| DASH | 01-05-2017 | 21-01-2022 | 7.96 | 46.72 | 246.17 |
| ZRX | 01-09-2017 | 21-01-2022 | 12.58 | 65.11 | 198.84 |
| DAI | 07-04-2018 | 21-01-2022 | -0.36 | 2.82 | 167.95 |
| MKR | 01-06-2018 | 21-01-2022 | 7.78 | 37.37 | 152.83 |
| ONT | 01-05-2018 | 02-06-2021 | 0.51 | 34.29 | 152.20 |
| QTUM | 01-04-2018 | 21-01-2022 | 4.92 | 36.71 | 120.24 |
| KNC | 01-06-2018 | 21-01-2022 | 6.98 | 39.72 | 91.99 |
| ZIL | 07-06-2018 | 21-01-2022 | 700.34 | 4542.14 | 90.96 |
| ICX | 01-10-2017 | 21-01-2022 | 19.57 | 78.58 | 77.05 |
| XEM | 01-06-2017 | 02-06-2021 | 12.54 | 70.73 | 72.29 |
| IOST | 06-06-2018 | 02-06-2021 | 1002.79 | 5967.86 | 67.78 |
| SC | 01-11-2019 | 21-01-2022 | 18.73 | 54.07 | 63.48 |
| BAT | 08-01-2018 | 21-01-2022 | 7.29 | 42.11 | 60.55 |
| BTG | 01-11-2017 | 21-01-2022 | 4.91 | 44.72 | 56.43 |
| BNT | 01-08-2017 | 21-01-2022 | 9.40 | 49.34 | 51.19 |
| REP | 02-01-2017 | 21-01-2022 | 10.28 | 53.01 | 30.55 |
| WAVES | 01-09-2019 | 21-01-2022 | 16.93 | 45.51 | 20.61 |
| LSK | 01-02-2018 | 21-01-2022 | 0.92 | 38.15 | 19.06 |
| VET | 01-09-2018 | 21-01-2022 | 11.23 | 42.87 | 13.67 |
| PAX | 04-12-2018 | 21-01-2022 | -0.08 | 1.51 | 7.18 |
| SNT | 01-01-2018 | 21-01-2022 | 2.98 | 34.79 | 6.54 |
| CVC | 01-07-2017 | 21-01-2022 | 13.21 | 65.33 | 4.60 |
| MAID | 02-06-2017 | 02-06-2021 | 8.64 | 42.59 | 4.09 |
| XVG | 01-10-2017 | 21-01-2022 | 70.59 | 492.34 | 3.79 |
| UTK | 07-02-2018 | 21-01-2022 | 10.05 | 56.90 | 3.62 |
| FUN | 01-09-2017 | 21-01-2022 | 11.14 | 77.26 | 1.77 |
| DCR | 08-05-2019 | 21-01-2022 | 8.31 | 35.72 | 0.61 |
| HT | 06-03-2019 | 02-06-2021 | 9.28 | 32.23 | 0.24 |
| ETH-BTC | 01-01-2017 | 21-01-2022 | 9.71 | 49.67 | 0.15 |

Table 2.1: Statistical Properties of Currency Data

First, we must examine the heterogeneity of returns in the cryptocurrency investment universe. To do this, we will build on the work of Ardia and Boudt (2018). The difference in the performance of two cryptocurrencies is defined as follows:

$$\hat{\Delta}_{i-j} = \frac{1}{T}\left(\sum_{t=1}^{T}(r_{i,t} - r_{j,t}) - \hat{\beta}'_{i-j} f_t\right). \tag{2.2}$$

Here, $\hat{\Delta} i - j$ represents the estimated difference in performance between cryptocurrency i and j, $\hat{\beta}' i - j$ represents the ordinary least square estimate of $(K \times 1)$ factor exposures, $f_t$ is the $(K \times 1)$ vector of risk factors at time $t$ where $t = 1, \ldots, T$, and $r_{i,t}$ is the $i^{th}$ cryptocurrency's return at time $t$.

The p-values are defined as:

$$\hat{p}_{i-j} = 2\hat{F}_{i-j}(-|\hat{\tau}_{i-j}|) . \tag{2.3}$$

Here, $\hat{p}_{i-j}$ represents the estimated p values obtained from probability integral transform of minus the absolute value of $\tau_{i-j}$ under $H_0$ [Null Hypothesis of equal performance], $\hat{\tau}_{i-j}$ is the estimate of studentized test statistic such that when its absolute value is higher the evidence against $H_0$ of equal performance is greater, and $\hat{F}_{i-j}$ is the consistent estimate of the true cumulative distribution function $F_{i-j}$ of $\tau_{i-j}$ under $H_0$.

Ardia and Boudt (2018) analyze whether the investor benefits from selecting top quintile funds using the outperformance $(\pi_i^+)$ and underperformance ratios $(\pi_i^-)$ in comparison to using the fund's estimated alpha. They use portfolio sorts to investigate this. The study uses the top quintile portfolio in terms of the outperformance ratio $(\pi_i^+)$ to construct a portfolio of top-performing funds and the top quintile portfolio in terms of the underperformance ratio $(\pi_i^-)$ to construct a portfolio of bottom-performing funds. The research finds that selecting funds using the outperformance ratio leads to a higher annualized return and alpha compared to using the fund's alpha or the t-statistic of the estimated alpha. They also find that restricting the peer group to the same investment style improves performance.

## 2.2 Defining Measures Used in Analysis

To compute peer performance ratios in the cryptocurrency universe, we use three measures: excess returns or average returns differential measure, Sharpe ratio, and modified Sharpe ratio, and evaluate their performance by implementing the rolling window strategy.

The alpha measure (excess returns in the context of the cryptocurrency market) is a commonly used industry standard for measuring the risk-adjusted performance of hedge funds. It was first introduced by Treynor and Black (1973) and later modified by Carhart (1997) and Fung and Hsieh (2004). Ardia and Boudt (2018) propose to use the alpha measure in conjunction with a new metric called the fund's alpha outperformance ratio ($\hat{\pi}^+_{i,\alpha}$), which is defined as the percentage of funds with a significantly lower alpha, where they define the corresponding estimator as $\hat{\tau}^+_i$

$$\hat{\tau}^+_i = \frac{1}{n}\sum_{j\neq i} I\{\hat{\tau}_{i-j} \geq \hat{q}^{\gamma^+}_{i-j}\}. \tag{2.4}$$

Here, $\hat{\tau}_{i-j}$ is the test statistic for outperformance ratio ($\pi^+_i$), $I(.)$ is the indicator function, $\hat{q}^{\gamma^+}_{i-j}$ represents the left-sided threshold that is used to compute the underperformance ratio as a percentage of cryptocurrencies for which $\hat{\tau}_{i-j} \geq \hat{q}^{\gamma^+}_{i-j}$. $\gamma^+$ is a value in the range of 95% or 90%. n is the total number of cryptocurrencies in the investment universe (for the analysis here, it will be 53).

The Sharpe ratio (Sharpe, 1992) is one industry standard for measuring the absolute risk-adjusted performance of hedge funds. It is calculated by dividing the investment's excess return over the risk-free rate by the volatility of the investment. The Sharpe ratio measures the return on an investment relative to its risk. Specifically, it compares the excess return of an investment over the risk-free rate (usually the T-bill rate) to the volatility of the investment's returns. A higher Sharpe ratio indicates that an investment has provided a higher level of return for the same level of risk or a lower level of risk for the same level of return. In his paper, Sharpe emphasizes that the Sharpe ratio is a measure of the risk-adjusted performance of an investment and not a measure of risk or return by itself. It is commonly used to evaluate the performance of mutual funds, hedge funds, and other types of investments and is considered a widely accepted standard for measuring risk-adjusted performance. Following the method proposed in Ardia and Boudt (2018) we will also be using an outperformance ratio based on the Sharpe ratio ($\hat{\pi}^{+}_{i,Sharpe}$).

Favre and Galeano (2002) propose a modified version of the Sharpe ratio that accounts for the skewness and kurtosis of the investment's returns. Skewness is a measure of the asymmetry of a distribution, while kurtosis is a measure of the 'peakedness' of a distribution. The modified Sharpe ratio is calculated by dividing the investment's excess return over the risk-free rate by a modified measure of volatility that considers the skewness and kurtosis of the investment's returns. Favre and Galeano (2002) argue that the traditional Sharpe ratio does not fully capture the risk-adjusted performance of an investment, particularly when the distribution of returns is not normal. By accounting for skewness and kurtosis, the modified Sharpe ratio is likely to provide a more accurate measure of the risk-adjusted performance of an investment. Based on similar reasoning, one of the rolling window strategies will be based on an outperformance ratio based on a modified Sharpe ratio ($\hat{\pi}^{+}_{i,M-Sharpe}$).

## 2.3 Implementation of Investment Strategy based on Estimators

To evaluate the usefulness of the information provided by the peer performance ratio, a 5-year monthly rolling window investment strategy is implemented on a universe of 53 cryptocurrencies using the real-world price data from 2017 to 2021. The parameters [Average Returns differential, Sharpe ratio, Modified Sharpe Ratio] and corresponding Peer performance ratios are calculated for the universe of 53 currencies for the trailing period of 12 months.

As proposed in Ardia and Boudt (2018) we implement a two-step estimation procedure for measuring the peer performance of a cryptocurrency in a universe of 53 currencies. The estimator uses a combination of pairwise and multiple testing to estimate the proportion of funds that have equal, lower, or greater risk-adjusted performance than the focal cryptocurrency. The three estimators are (i) $\pi^{0}_{i}$: the proportion of cryptocurrencies in the peer group that perform equally well as cryptocurrency i, (ii) $\pi^{+}_{i}$: the proportion of cryptocurrencies in the peer group that is outperformed by crypto currency $i$, and (iii) $\pi_i^-$: the proportion of cryptocurrencies in the peer group that outperforms cryptocurrency i. The equal performance ratio ($\hat{\pi}_i^0$) is defined as follows:

$$\hat{n}_i^0 = c_i^0 min\{\frac{\sum_{j\neq i} I\{\hat{p}_{i-j} \geq \lambda_i\}}{1-\lambda_i}, n\}. \tag{2.5}$$

Here, $\hat{n}_i^0$ is a natural estimator for the number of peer funds that perform equally well as the focal fund. $I(.)$ is the indicator function, $\hat{p}_{i-j}$ is the estimated p-value for a cryptocurrency pair (i,j), n is the number of cryptocurrencies, $\lambda_i$ is a threshold value which is effective for categorizing two sides with different performances. $c_i^0$ is the correction factor that adjusts bias induced by truncation.

$$\hat{\pi}_i^0 = \frac{\hat{n}_i^0}{n}. \tag{2.6}$$

Here, $\hat{\pi}_i^0$ is the corresponding estimation for equal performance ratio obtained by using the estimated value of $\hat{n}_i^0$.

Where the outperformance ($\hat{\pi}_i^+$) and underperformance ($\hat{\pi}_i^-$) ratios, are mathematically defined as:

$$\hat{\pi}_i^+ = \begin{cases} \frac{1}{n} max\{\sum_{j\neq i} I\{\hat{\tau}_{i-j} \geq \hat{q}_{i-j}^{\gamma^+}\} - \hat{n}_i^0(1-\gamma^+), 0\} & \text{if } \sum_{j\neq i} I\{\hat{\Delta}_{i-j} \geq 0\} \geq \frac{n}{2} \\ 1 - \hat{\pi}_i^0 - \hat{\pi}_i^- & \text{otherwise.} \end{cases} \tag{2.7}$$

$$\hat{\pi}_i^- = \begin{cases} \frac{1}{n} max\{\sum_{j\neq i} I\{\hat{\tau}_{i-j} \leq \hat{q}_{i-j}^{\gamma^-}\} - \hat{n}_i^0\gamma^-, 0\} & \text{if } \sum_{j\neq i} I\{\hat{\Delta}_{i-j} \geq 0\} < \frac{n}{2} \\ 1 - \hat{\pi}_i^0 - \hat{\pi}_i^+ & \text{otherwise.} \end{cases} \tag{2.8}$$

Here, $\hat{\pi}_i^+$ represents the outperformance ratio for fund $i$ and $\hat{\pi}_i^-$ represents underperformance ratio for fund $i$, where they explicitly adjust for false positives by subtracting term $\hat{n}_i^0(1-\gamma^+)$ and $\hat{n}_i^0\gamma^-$ respectively. To avoid false negatives we have $\gamma^+ = 0.4$ and to avoid false positives we have $\gamma^- = 0.6$.

The strengths of the proposed method are that it uses a threshold of statistical significance to determine the relative performance between two cryptocurrencies, and it uses a false discovery rate methodology to obtain peer performance estimates that are robust to false positives. The method defines a universe with a total of n+1 cryptocurrencies [Here 53 are used for implementation purposes], and it uses risk-adjusted performance, which is typically estimated by the intercept of the least squares regression of the cryptocurrency returns on a series of risk factors.

Once the pairwise tests have been completed, the false discovery rate (FDR) approach proposed by Storey (2002) is used to determine the proportions of funds that are over-performing, underperforming, or performing equally in terms of average returns differential measure. The FDR approach is used to correct for the possibility that a cryptocurrency may have significantly higher excess returns due to luck.

$$\begin{aligned}
n_i^+ &= \sum_{j \neq i} I\{\Delta_{i-j} > 0\} \\
&= \sum_{j \neq i} I\{\hat{\tau}_{i-j} \geq -\hat{q}_{i-j}^{\gamma^+}\} \\
&\quad \underbrace{- \underbrace{\sum_{j \neq i \cup \Delta_{i-j}=0} I\{\hat{\tau}_{i-j} \geq -\hat{q}_{i-j}^{\gamma^+}\}}_{\approx n_i^0(1-\gamma^+)} - \sum_{j \neq i \cup \Delta_{i-j}<0} I\{\hat{\tau}_{i-j} \geq -\hat{q}_{i-j}^{\gamma^+}\}}_{false\ positives} \\
&\quad + \underbrace{\sum_{j \neq i \cup \Delta_{i-j}>0} I\{\hat{\tau}_{i-j} \geq -\hat{q}_{i-j}^{\gamma^+}\}}_{false\ negatives} \\
&\approx \sum_{j \neq i} I\{\hat{\tau}_{i-j} \geq -\hat{q}_{i-j}^{\gamma^+}\} - n_i^0(1-\gamma^+).
\end{aligned} \tag{2.9}$$

Here, $n_i^+$ represents the number of cryptocurrencies that are outperformed by the focal cryptocurrency $i$ and those that outperform cryptocurrency $i$, $n_i^-$ where the latter can be figured out after obtaining $n_i^+$ using the relation $n_i^+ + n_i^- = n - n_i^0$. $\hat{\tau}_{i-j}$ is the studentized test statistic given by relation $\hat{\tau}_{i-j} = \hat{\Delta}_{i-j}/\hat{se}_{i-j}$ where $\hat{se}_{i-j}$ is the standard error. ${\gamma^+}_{i-j}$ stands for one sided confidence level.

The method uses p-values from two-sided tests of the null hypothesis of equal performance. It exploits the difference in the distribution of p-values when the null hypothesis is true or false. The key result is that under suitable assumptions, the expected number of p-values exceeding a threshold $\lambda_i$ is $(1-\lambda_i)n_i^0$, where $n_i^0$ is the number of peer currencies that perform equally well as the focal cryptocurrency. The study uses this result to estimate the proportion of equal performance by calculating the number of estimated p-values exceeding $\lambda_i$, divided by $(1-\lambda_i)$ and adjusting for bias. The choice of threshold $\lambda_i$ balances the trade-off between the satisfaction of assumptions and the number of observations used in the estimation.

## 2.4 Heterogeneity in Returns Using the Screening Plot

These six graphs are designed to showcase the performance of cryptocurrencies using three key metrics: excess return or average return differential, Sharpe ratio, and modified Sharpe ratio. Each graph is divided into two parts, with the left side depicting the metric for all cryptocurrencies sorted in descending order based on their performance in the entire investment universe. The right side presents a screening plot using the peer performance ratio based on the corresponding metric, highlighting outperformance ($\hat{\pi}^+$), underperformance ($\hat{\pi}^-$), and equal performance ($\hat{\pi}^0$) of the cryptocurrencies compared to the investment universe. The plots are presented for daily and weekly return frequencies to evaluate the presence of heterogeneity in returns and the impact of the granularity of returns data on investment decisions.

## Daily Analysis

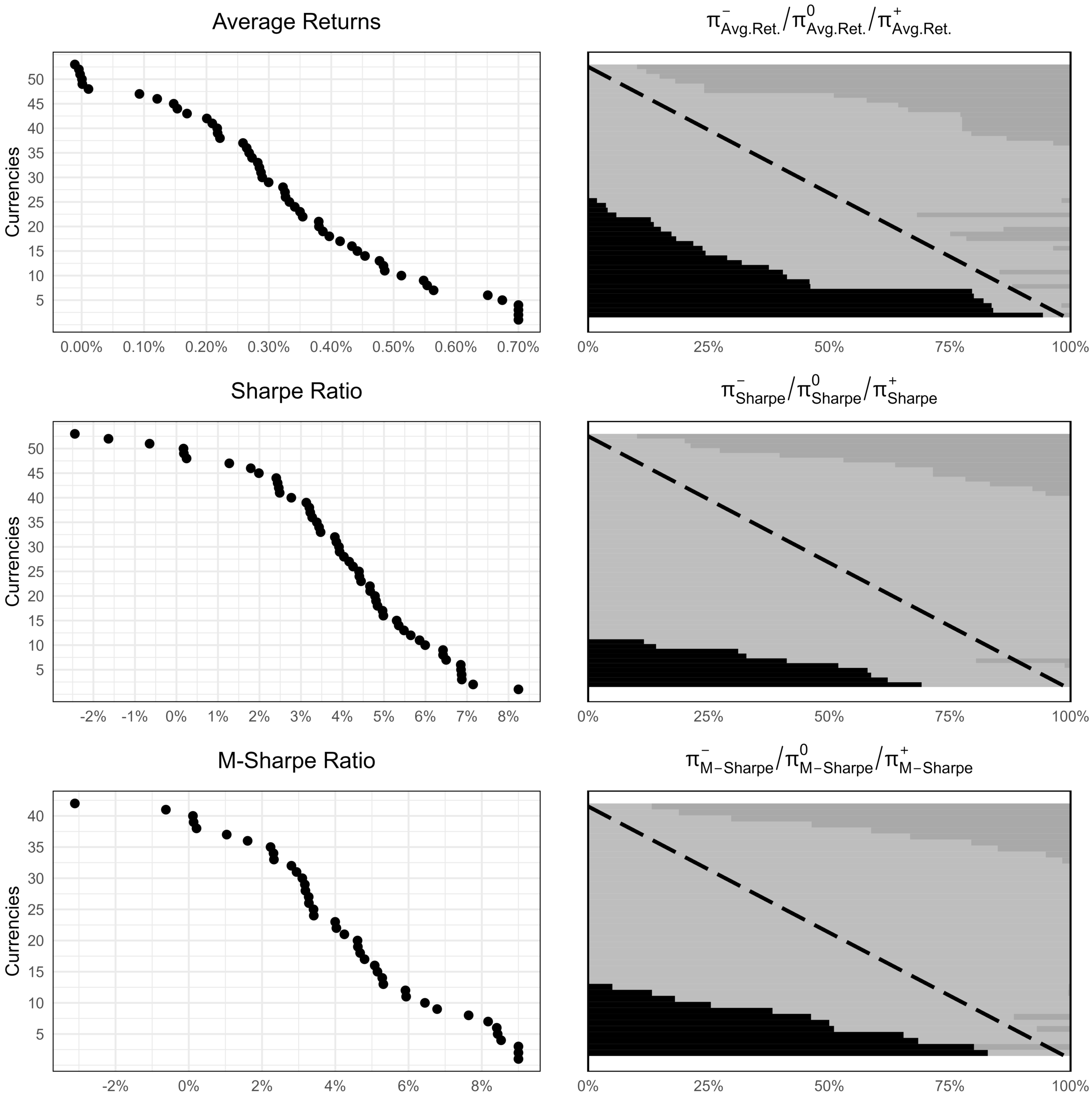


Figure 2.1: The combined figure presents the performance metrics of cryptocurrencies in the investment universe using daily return frequency. The left column displays the sorted performance based on excess return or average return differential, Sharpe ratio, and Modified Sharpe ratio [Value at Risk Level = 0.95] from top to bottom, respectively. The corresponding screening plots on the right highlight the outperformance ($\hat{\pi}^+$) [black], equal performance ($\hat{\pi}^0$) [light grey], and underperformance ($\hat{\pi}^-$) [dark grey] of cryptocurrencies for each metric. The presence of outperformance in the bottom left and underperformance in the top right regions consistently indicates the existence of heterogeneous returns, suggesting that active selection can help capture excess returns over time.

## Weekly Analysis

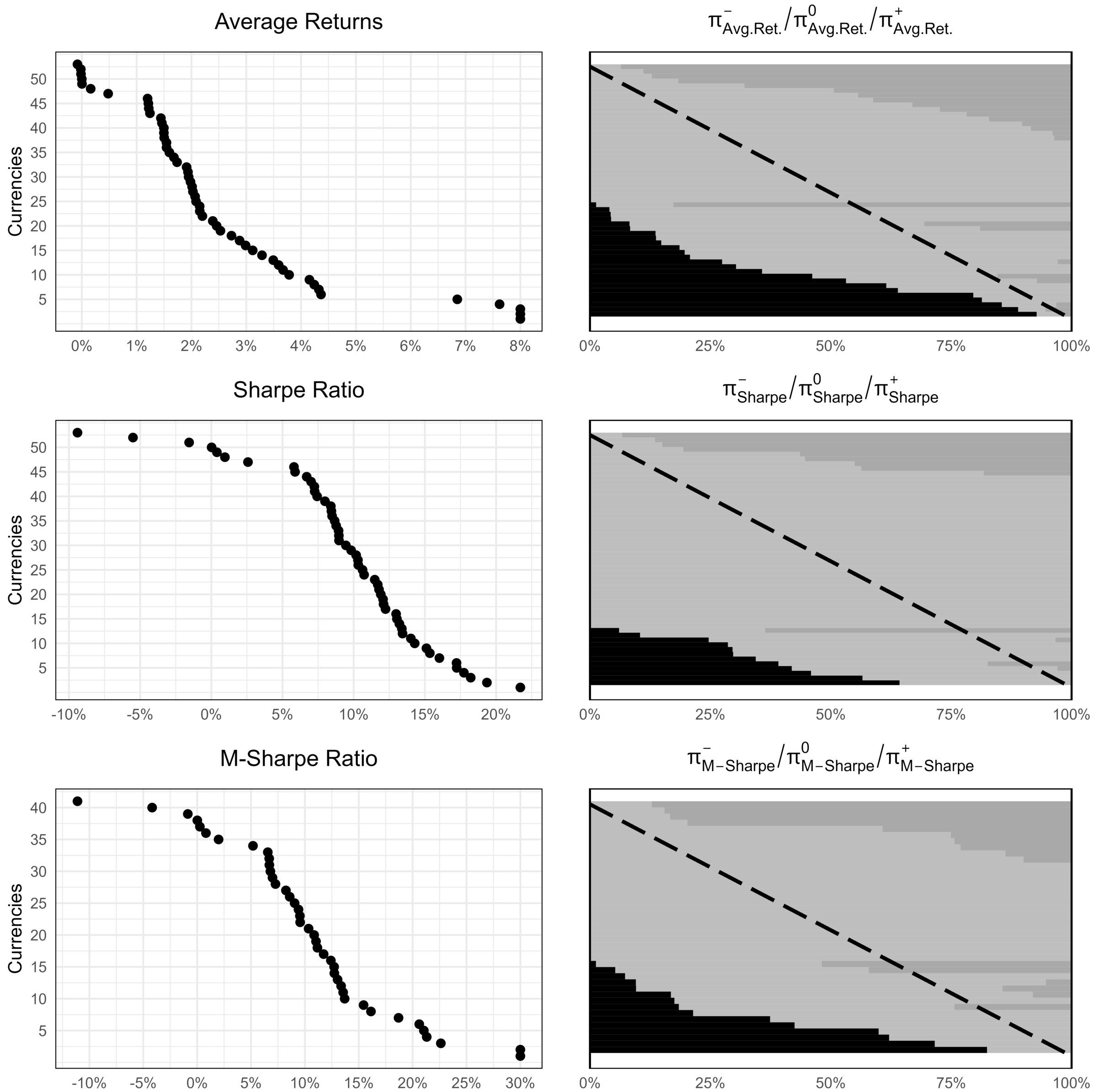


Figure 2.2: The combined figure presents the performance metrics of cryptocurrencies in the investment universe using weekly return frequency. The left column displays the sorted performance based on excess return or average return differential, Sharpe ratio, and Modified Sharpe ratio [Value at Risk Level = 0.95] from top to bottom, respectively. The corresponding screening plots on the right highlight the outperformance ($\hat{\pi}^+$) [black], equal performance ($\hat{\pi}^0$) [light grey], and underperformance ($\hat{\pi}^-$) [dark grey] of cryptocurrencies for each metric. The presence of outperformance in the bottom left and underperformance in the top right regions consistently indicates the existence of heterogeneous returns, suggesting that active selection can help capture excess returns over time.

# Chapter 3

# Investment Strategy Analysis

## 3.1 Obtaining Daily Returns Data

The analysis commences by utilizing the daily returns data for the 53 cryptocurrencies within the selected time frame of 2017 to 2021. The daily returns are calculated over a five-year period for the 53 cryptocurrencies, employing the evolution of the closing price from the last transaction of the respective day. This process generates a 1826x53 matrix encompassing the corresponding daily returns data for 60 months, or five years, for the 53 cryptocurrencies, thereby rendering it highly computationally efficient for the execution of subsequent mathematical operations. This matrix $[R_m]$ obtained using the equation (2.1) is subsequently exported as an RDA file, which is utilized for implementing rolling window investment strategies. The relatively smaller file size, containing only the requisite information, facilitates expedited processing times.

## 3.2 Rolling Window Analysis on Returns Data for 2017-2021

A rolling window investment analysis is proposed to evaluate the effectiveness of peer performance ratios in the context of investment strategies. This method has been widely used in finance research and practice (Fama and French, 1993). In this analysis, trailing 1-year data is used for the calculation of the metric [excess return or average return differential, Sharpe ratio (Sharpe, 1966), modified Sharpe ratio (Sortino and Price, 1994) and corresponding peer performance ratio based on that metric. Rolling window analysis allows for a dynamic assessment of performance and adaptability to changing market conditions, which is essential for robust investment strategies (Ledoit and Wolf, 2008; Bali et al., 2009).

Outperformance ratios for the given time interval are evaluated, and the top 10 percent [top 5 currencies in the universe of 53 currencies] are identified for investment for the following period. The implementation considers daily, weekly, and monthly rebalancing frequencies. The weights of the corresponding investments in the top 10 percent performers are decided based on the outperformance ratios, i.e., the weighted average of the $\pi^+$.

$$w_{i,t} = \frac{\pi^+_{i,t}}{\sum_{i=1}^{P^t_{10}} \pi^+_{i,t}}. \tag{3.1}$$

Here, $w_{i,t}$ represents the weight for cryptocurrency $i$ that will be allocated in the investment basket for the following period containing out-of-sample returns data. $\pi^+_{i,t}$ is the outperformance ratio for the period time t for cryptocurrency $i$, and $P^t_{10}$ represents the set of top 10 percent cryptocurrencies chosen for the investment basket in the rolling window.

For a strategy $S$, returns for that time period can be written as:

$$R_{t,S} = \sum_{i=1}^{P_{10}} w_{i,t} R_{i,c_{P_{10}},\tau}. \tag{3.2}$$

Here, $R_{t,S}$ represents the returns for the period $t$ for the portfolio using strategy $S$, which here for the current analysis can be one of three based on Alpha measure, Sharpe ratio, and Modified Sharpe ratio. $w_{i,t}$ are the weights obtained using the weighted average from the previous equation, and $R_{i,c_{P_{10}},t}$ are the returns for cryptocurrency $i$ for the out-of-sample period $\tau$ in the top 10 percent cryptocurrency investment basket corresponding to that rolling window.

In this analysis, benchmark portfolio selections are carried out using three metrics: Average Returns differential, Sharpe ratio, and Modified Sharpe ratio. These metrics are employed for selecting the top 10 percent cryptocurrencies (top 5 currencies in the universe of 53 currencies) for investment in the following period. The implementation considers daily, weekly, and monthly rebalancing frequencies. The selections are then equal-weighted to calculate the corresponding out-of-sample returns for the benchmark portfolio for that period.

The out-of-sample returns data for the following period is stored, and the rolling window is shifted forward to recalculate the peer performance ratios for the corresponding parameters [Alpha, Sharpe ratio, and Modified Sharpe Ratio] at the chosen rebalancing frequency (daily, weekly, or monthly). The process is repeated for five years to obtain the returns for an investment strategy based on the top 10 percent [$P_{10}$] performers based on the outperformance ratio [$\pi^{+}_{i,t}$] for a corresponding parameter. Computation of the peer performance ratios using the Returns Matrix is handled by the functionality provided by the Peer Performance R package. The package is responsible for providing the relevant values of the measures and Outperformance ratios. The results of implementing this investment strategy with different rebalancing frequencies are presented in the following chapter, with the statistical analysis of returns using various performance metrics.

The following three plots will help understand the performance of these strategies under the daily rebalancing frequency, with each plot having cumulative returns on the top panel and drawdowns on the bottom panel. The plots are based on the three metrics: average return differential, Sharpe ratio, and modified Sharpe ratio. They are presented for daily rebalancing frequency.

The purpose of plotting drawdowns alongside cumulative returns is to evaluate the downside risk, an essential aspect of assessing the overall investment strategy's risk and performance (Bali et al., 2009). Drawdowns provide insight into the magnitude and duration of losses experienced by the investment strategy during unfavorable market conditions, which is crucial for investors seeking to manage and mitigate risks in their portfolios.

## Cumulative Wealth

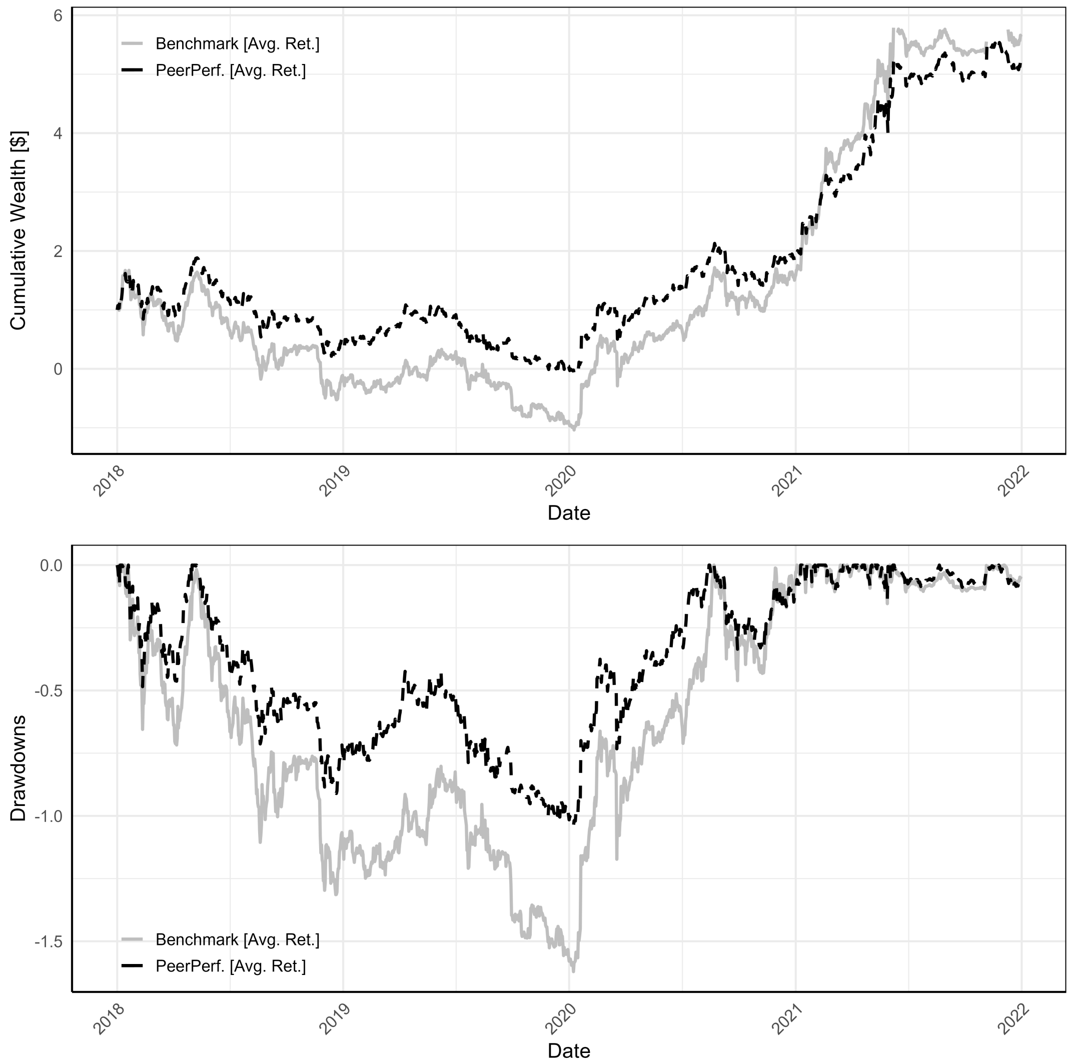


Figure 3.1: illustrates the performance of the peer performance strategy and the benchmark strategy based on the average return differential. The top panel shows the cumulative returns for 1 USD Notional of both strategies, while the bottom panel presents their drawdowns. This figure allows for a comparison of the overall performance and downside risk of the two strategies using this particular metric.

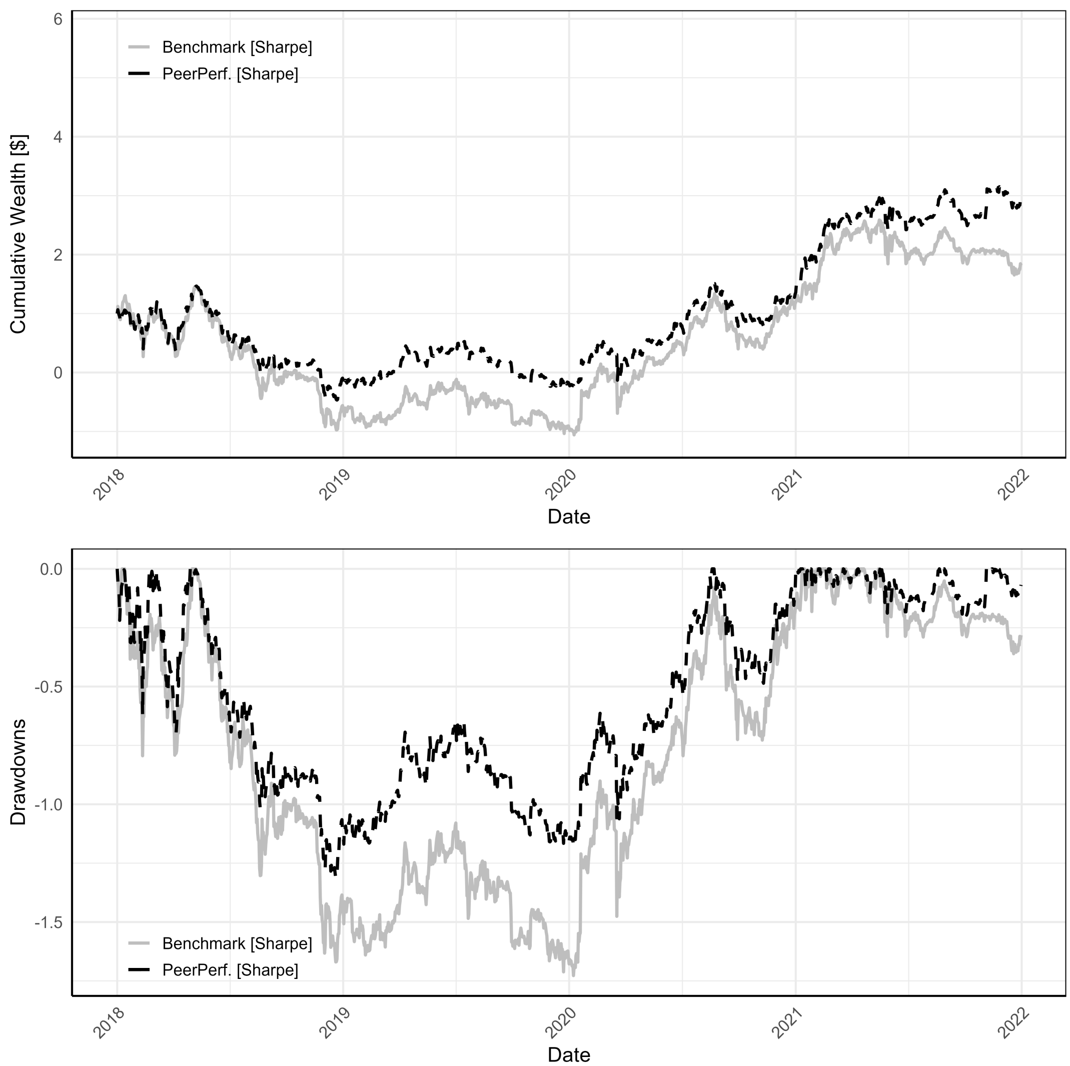


Figure 3.2: illustrates the performance of the peer performance strategy and the benchmark strategy based on the Sharpe Ratio factor. The top panel shows the cumulative returns for 1 USD Notional of both strategies, while the bottom panel presents their drawdowns. This figure allows for a comparison of the overall performance and downside risk of the two strategies using this particular metric.

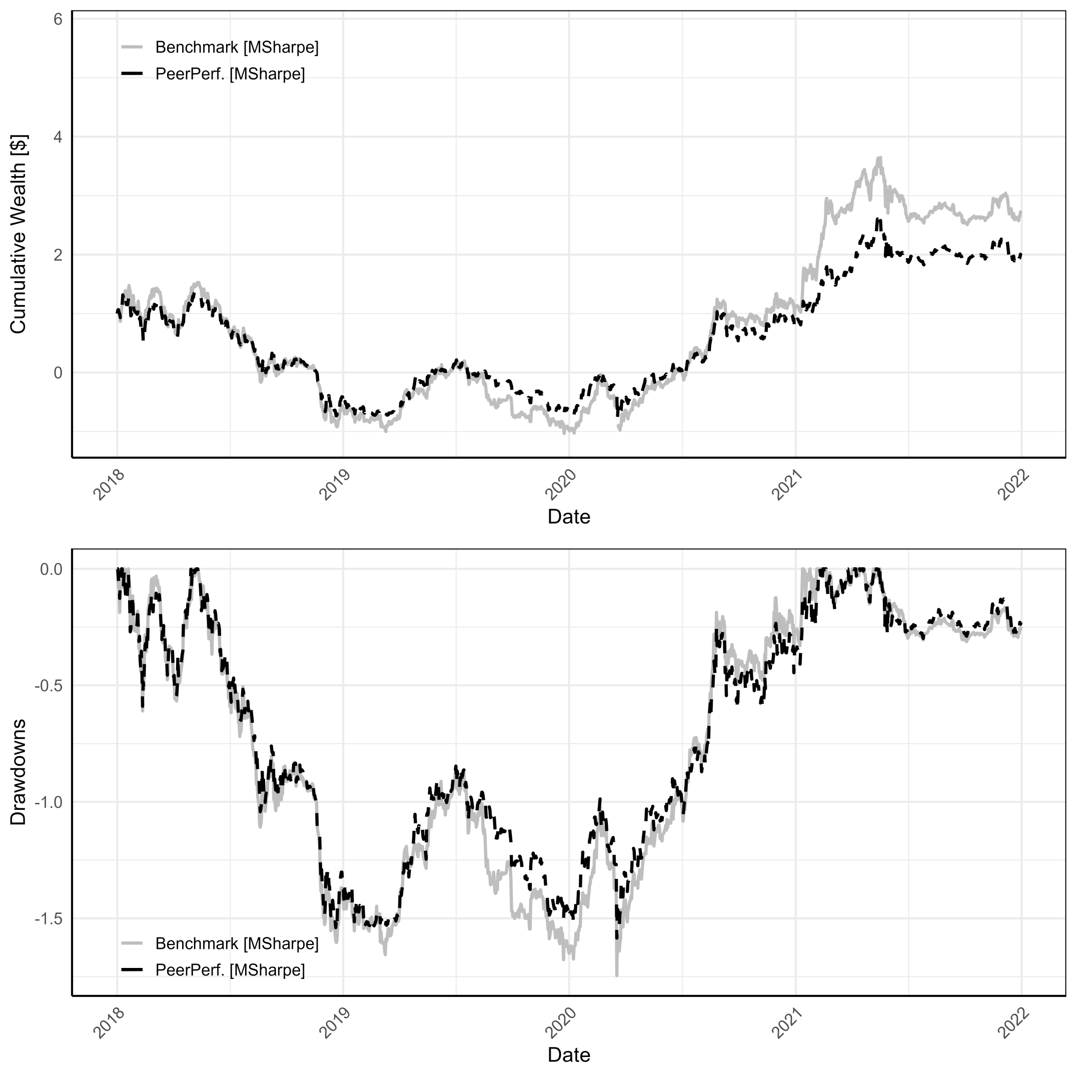


Figure 3.3: illustrates the performance of the peer performance strategy and the benchmark strategy based on the Modified Sharpe Ratio factor. The top panel shows the cumulative returns for 1 USD Notional of both strategies, while the bottom panel presents their drawdowns. This figure allows for a comparison of the overall performance and downside risk of the two strategies using this particular metric.

Following this, we evaluate the performance of these investment strategies using various performance metrics in the next chapter.

# Chapter 4

# Performance Analysis of Implemented Strategies

## Returns Statistics

Table 4.1 presents return statistics for the three investment strategies based on outperformance ratios using the average returns factor, Sharpe ratio factor, and modified Sharpe ratio factor, as well as their corresponding benchmarks across daily, weekly, and monthly frequencies.

For the average returns factor (Panel A), the peer performance strategy consistently outperforms the benchmark strategy in terms of the Sharpe ratio and the modified Sharpe ratio, indicating that it provides better risk-adjusted returns (Sharpe (1966)). However, the annualized mean return of the peer performance strategy is slightly lower than that of the benchmark strategy, suggesting a trade-off between risk and return (Markowitz (1952)). This trade-off is more pronounced at the monthly frequency, where the peer performance strategy has a lower annualized mean return and similar risk-adjusted performance as the benchmark strategy.

The Sharpe ratio factor (Panel B) shows a clear outperformance of the peer performance strategy over the benchmark strategy across all frequencies. The peer performance strategy has higher annualized mean returns, lower annualized standard deviations, and better risk-adjusted performance than the benchmark strategy. This suggests that the Sharpe ratio factor is effective in capturing the risk-return trade-offs in the cryptocurrency market (Sharpe (1966)).

The modified Sharpe ratio factor (Panel C) shows mixed results. While the benchmark strategy outperforms the peer performance strategy regarding the annualized mean return and risk-adjusted performance at the daily and monthly frequencies, the peer performance strategy has a lower annualized standard deviation. At the weekly frequency, the benchmark strategy has a higher annualized mean return and better risk-adjusted performance but also a higher annualized standard deviation. The mixed results for the modified Sharpe ratio factor may be due to the fact that it incorporates higher moments of the return distribution, which can be sensitive to the estimation method and sample period (Lo (2002)).

In summary, the effectiveness of investment strategies based on outperformance ratios varies across factors and frequencies. The Sharpe ratio factor appears to be the most promising, as it consistently leads to better risk-adjusted performance for the peer performance strategy compared to the benchmark strategy. However, further research is needed to understand the robustness of these findings, so we move on to evaluating drawdown statistics for these strategies.

| Strategy | Mean [Annualized] (%) | Standard Deviation [Annualized](%) | Minimum (%) | Maximum (%) | Sharpe Ratio [Annualized] | M-Sharpe Ratio [Annualized] |
|---|---|---|---|---|---|---|
| **Panel A: Average Returns Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 115.22 | 144.18 | -56.33 | 70.18 | 0.80 | 2.19 |
| Peer Performance | 104.00 | 120.08 | -46.09 | 60.11 | 0.87 | 3.91 |
| **Weekly** | | | | | | |
| Benchmark | 99.25 | 128.48 | -67.55 | 51.20 | 0.77 | 0.71 |
| Peer Performance | 101.60 | 105.16 | -47.22 | 44.37 | 0.97 | 0.92 |
| **Monthly** | | | | | | |
| Benchmark | 101.55 | 121.73 | -70.80 | 133.97 | 0.83 | 1.01 |
| Peer Performance | 85.23 | 104.52 | -56.97 | 113.57 | 0.82 | 0.96 |
| **Panel B: Sharpe Ratio Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 21.13 | 123.41 | -52.52 | 48.79 | 0.17 | 0.22 |
| Peer Performance | 47.72 | 102.33 | -43.47 | 33.02 | 0.47 | 0.59 |
| **Weekly** | | | | | | |
| Benchmark | 24.74 | 115.68 | -61.02 | 46.87 | 0.21 | 0.18 |
| Peer Performance | 55.43 | 97.31 | -57.40 | 38.11 | 0.57 | 0.51 |
| **Monthly** | | | | | | |
| Benchmark | 35.52 | 104.30 | -80.40 | 73.54 | 0.34 | 0.28 |
| Peer Performance | 34.69 | 86.04 | -58.94 | 58.16 | 0.40 | 0.33 |
| **Panel C: M-Sharpe Ratio Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 42.96 | 125.39 | -55.67 | 34.23 | 0.34 | 0.44 |
| Peer Performance | 24.81 | 101.51 | -43.25 | 30.89 | 0.24 | 0.31 |
| **Weekly** | | | | | | |
| Benchmark | 59.52 | 112.50 | -50.54 | 51.66 | 0.53 | 0.47 |
| Peer Performance | 40.40 | 92.09 | -43.92 | 38.52 | 0.44 | 0.39 |
| **Monthly** | | | | | | |
| Benchmark | 44.87 | 108.98 | -80.84 | 60.97 | 0.41 | 0.34 |
| Peer Performance | 32.40 | 87.62 | -67.92 | 44.45 | 0.37 | 0.30 |

Table 4.1: Returns Statistics

## Drawdown Statistics

Based on the drawdown statistics presented in the table 4.2, we can analyze the performance of the three investment strategies (Average Returns Factor, Sharpe Ratio Factor, and M-Sharpe Ratio Factor) on daily, weekly, and monthly frequencies. Our analysis will consider the Cumulative Returns, CAGR, Max Drawdown, Average Drawdown, Sortino Ratio, and Pain Index as key metrics.

Maximum drawdown is the most significant percentage decline in the value of an investment strategy from its peak to its trough. It measures the worst-case loss that an investor would have experienced during a specific period, indicating the strategy's downside risk.

$$MDD = \max_{t \in T} \left( \max_{s \geq t} V_s - V_t \right). \tag{4.1}$$

Here, $MDD$ represents the Maximum drawdown, $T$ is the period under consideration, and $V_t$ is the value of the investment strategy at time $t$.

Average drawdown is the mean of all the drawdowns experienced by an investment strategy during a specific period. It measures the typical loss an investor would have experienced while investing in the strategy, capturing the average downside risk.

$$ADD = \frac{\sum_{i=1}^{n} D_i}{n}. \tag{4.2}$$

Here, $ADD$ represents the Average drawdown, $D_i$ is the drawdown at period $i$, and $n$ is the total number of drawdowns during the period.

The Sortino Ratio is a risk-adjusted performance metric that evaluates the excess return of an investment strategy per unit of downside risk (Sortino and Price, 1994). It is an extension of the Sharpe ratio, focusing specifically on downside volatility instead of total volatility.

$$Sortino = \frac{R_p - R_f}{\sigma_d}. \tag{4.3}$$

Here, $R_p$ is the average return of the investment strategy, $R_f$ is the risk-free rate, and $\sigma_d$ is the downside deviation, which is the standard deviation of the negative returns.

The Pain Index, also known as the Ulcer Index, measures the depth and duration of drawdowns experienced by an investment strategy (Martin (1987)). It provides a comprehensive view of the downside risk, taking both the magnitude and the persistence of losses into account.

$$PI = \sqrt{\frac{\sum_{t=1}^{T} (1 - \frac{V_t}{\max_{s \leq t} V_s})^2}{T}}. \tag{4.4}$$

Here, $PI$ represents the Pain Index, $T$ is the period under consideration, and $V_t$ is the value of the investment strategy at time $t$.

Upon careful examination of the drawdown statistics presented in Table 4.2, we can conduct an in-depth analysis of the performance of the three investment strategies—Average

Returns Factor, Sharpe Ratio Factor, and M-Sharpe Ratio Factor—across daily, weekly, and monthly frequencies. The metrics under consideration include Cumulative Returns, Compound Annual Growth Rate (CAGR), Maximum Drawdown, Average Drawdown, Sortino Ratio, and Pain Index.

In Panel A, focusing on the Average Returns Factor, the peer performance strategy outperforms the benchmark strategy regarding lower maximum and average drawdowns across all frequencies. Notably, the daily frequency exhibits the highest Cumulative Annual Growth Rate (CAGR) and Sortino Ratio for both strategies, indicating superior risk-adjusted performance at this frequency, but in general, for the three frequencies, the benchmark strategy is producing better returns than peer performance-based strategy.

Panel B, which examines the Sharpe Ratio Factor, demonstrates that the peer performance strategy consistently surpasses the benchmark strategy with higher CAGRs and Sortino Ratios and lower maximum and average drawdowns across all frequencies. The weekly frequency emerges as the most effective for the peer performance strategy in this case, with the highest CAGR and Sortino Ratio.

Lastly, in Panel C, which considers the Modified Sharpe Ratio Factor, the benchmark strategy generally outperforms the peer performance strategy regarding CAGR, Sortino Ratio, and the Pain Index across all frequencies. However, the peer performance strategy exhibits lower maximum and average drawdowns.

In conclusion, the Sharpe Ratio Factor strategy consistently performs better across all frequencies, while the M-Sharpe Ratio Factor strategy shows mixed results. Although the Average Returns Factor strategy has higher Cumulative Returns, it has higher drawdowns and a lower Sortino Ratio, indicating higher risk exposure. The Sortino Ratio (Sortino, 1991) and Pain Index (Martin, 1987) are relevant finance concepts to consider when assessing the risk-adjusted performance of these strategies.

| Strategy | Cumulative Returns(%) | CAGR | Max Drawdown | Average Drawdown | Sortino Ratio [Annualized] | Pain Index |
|---|---|---|---|---|---|---|
| **Panel A: Average Returns Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 467.61 | 0.53 | 1.62 | 0.31 | 1.23 | 1.04 |
| Peer Performance | 422.08 | 0.50 | 1.04 | 0.23 | 1.36 | 0.73 |
| **Weekly** | | | | | | |
| Benchmark | 398.89 | 0.49 | 1.62 | 0.31 | 0.47 | 1.04 |
| Peer Performance | 408.35 | 0.50 | 1.04 | 0.23 | 0.52 | 0.73 |
| **Monthly** | | | | | | |
| Benchmark | 406.22 | 0.50 | 1.62 | 0.31 | 0.22 | 1.04 |
| Peer Performance | 340.91 | 0.45 | 1.04 | 0.23 | 0.25 | 0.73 |
| **Panel B: Sharpe Ratio Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 85.75 | 0.16 | 1.73 | 0.59 | 0.24 | 1.13 |
| Peer Performance | 193.65 | 0.30 | 1.32 | 0.58 | 0.67 | 0.79 |
| **Weekly** | | | | | | |
| Benchmark | 99.44 | 0.19 | 1.73 | 0.59 | 0.09 | 1.13 |
| Peer Performance | 222.77 | 0.34 | 1.32 | 0.58 | 0.25 | 0.79 |
| **Monthly** | | | | | | |
| Benchmark | 142.07 | 0.25 | 1.73 | 0.59 | 0.04 | 1.13 |
| Peer Performance | 138.75 | 0.24 | 1.32 | 0.58 | 0.12 | 0.79 |
| **Panel C: M-Sharpe Ratio Factor** | | | | | | |
| **Daily** | | | | | | |
| Benchmark | 174.34 | 0.28 | 1.75 | 0.35 | 0.48 | 1.21 |
| Peer Performance | 100.67 | 0.19 | 1.58 | 0.54 | 0.35 | 1.01 |
| **Weekly** | | | | | | |
| Benchmark | 239.21 | 0.36 | 1.75 | 0.35 | 0.18 | 1.21 |
| Peer Performance | 162.36 | 0.27 | 1.58 | 0.54 | 0.13 | 1.01 |
| **Monthly** | | | | | | |
| Benchmark | 179.49 | 0.29 | 1.75 | 0.35 | 0.09 | 1.21 |
| Peer Performance | 129.59 | 0.23 | 1.58 | 0.54 | 0.06 | 1.01 |

Table 4.2: Drawdown Statistics

## Risk-Adjusted Performance Statistics

The risk-adjusted performance statistics presented in Table 4.3 facilitate a comprehensive evaluation of the three investment strategies—Average Returns Factor, Sharpe Ratio Factor, and M-Sharpe Ratio Factor—across daily, weekly, and monthly frequencies. The metrics under scrutiny include Calmar Ratio, Value at Risk (VaR), Treynor Ratio, and Information Ratio.

The Calmar Ratio is a performance metric that measures the excess return of an investment strategy per unit of downside risk, specifically considering the maximum drawdown (Young, 1991). It is particularly useful for strategies with asymmetric return distributions and tail risk.

$$Calmar = \frac{R_p - R_f}{MDD}. \tag{4.5}$$

Here, $R_p$ is the average return of the investment strategy, $R_f$ is the risk-free rate [Assumed $R_f = 0$ for the calculation here], and $MDD$ is the maximum drawdown.

Value at Risk (VaR) is a widely used risk measure that estimates the maximum potential loss of an investment strategy over a specific time horizon and confidence level (Jorion (2000)). It provides a quantification of the tail risk associated with the strategy.

$$VaR_\alpha = F^{-1}(\alpha). \tag{4.6}$$

Here, $VaR_\alpha$ represents the Value at Risk at a given confidence level $\alpha$, and $F^{-1}(\alpha)$ is the inverse of the cumulative distribution function of the strategy's returns at the $\alpha$ quantile.

The Treynor Ratio is a risk-adjusted performance metric that evaluates the excess return of an investment strategy per unit of systematic risk, as measured by the strategy's beta with respect to the benchmark (Treynor (1965)). It is particularly useful for comparing the performance of strategies with different levels of market risk exposure.

$$Treynor = \frac{R_p - R_f}{\beta_{p,b}}. \tag{4.7}$$

Here, $R_p$ is the average return of the investment strategy, $R_f$ is the risk-free rate [Assumed $R_f = 0$ for the calculation here], and $\beta_{p,b}$ is the beta of the strategy with respect to the benchmark strategy returns.

The Information Ratio measures the excess return of an investment strategy relative to its benchmark per unit of tracking error, which is the standard deviation of the strategy's excess returns over the benchmark (Grinold (1989)). It helps investors evaluate the active management skills of the strategy and its ability to generate consistent alpha.

$$IR = \frac{R_p - R_b}{\sigma_{p-b}}. \tag{4.8}$$

Here, $R_p$ is the average return of the investment strategy, $R_b$ is the average return of the benchmark strategy, and $\sigma_{p-b}$ is the standard deviation of the strategy's excess returns over the benchmark.

In Panel A, concerning the Average Returns Factor, the peer performance strategy consistently outperforms the Benchmark strategy across all frequencies in terms of Calmar Ratio and Value-at-Risk (VaR). The weekly frequency demonstrates the highest Information Ratio, indicating superior performance consistency compared to the benchmark.

Panel B, which assesses the Sharpe Ratio Factor, reveals that the peer performance strategy delivers better results than the benchmark strategy in terms of VaR across all frequencies. Additionally, the peer performance strategy exhibits higher Information Ratios in all frequencies, with the weekly frequency showing the most favorable risk-adjusted performance. However, Treynor Ratios present mixed results, with the daily and monthly frequencies indicating negative values.

Finally, in Panel C, which evaluates the Modified Sharpe Ratio Factor, the peer performance strategy consistently demonstrates lower VaR and higher Information Ratios than the Benchmark strategy across all frequencies. However, the Treynor Ratios are negative for both strategies, suggesting that the excess returns over the benchmark are not commensurate with the risks taken.

The Sharpe Ratio Factor strategy consistently exhibits superior risk-adjusted performance, as evidenced by the Information Ratio across all frequencies. The Average Returns Factor and M-Sharpe Ratio Factor strategies demonstrate mixed results, with the former outperforming in most metrics but the latter presenting a more nuanced performance profile.

In summary, the peer performance investment strategy demonstrates considerable advantages over the Benchmark strategies in terms of risk-adjusted returns. The superiority of the peer performance strategy is evident across various metrics, including Calmar Ratio, Value at Risk (VaR), Treynor Ratio, and Information Ratio, which have been employed to evaluate the risk-return trade-off in the context of Average Returns Factor, Sharpe Ratio Factor, and M-Sharpe Ratio Factor strategies.

The Calmar Ratio, which represents the relationship between the Compound Annual

Growth Rate (CAGR) and maximum drawdown, showcases the peer performance ratio's ability to achieve higher returns relative to the risk of potential losses (Young (1991)). Similarly, the lower VaR exhibited by the peer performance strategy highlights reduced tail risk, which means that the likelihood of extreme losses is minimized (Jorion, 2000).

Furthermore, the peer performance strategy demonstrates superior Treynor Ratios, suggesting that it can achieve higher returns per unit of systematic risk (Treynor (1965)). The higher Information Ratios further corroborate this superior performance, indicating that the peer performance strategy can generate higher returns relative to the Benchmark for each unit of active risk (Goodwin (1998)).

Overall, the peer performance investment strategy outperforms the Benchmark strategies across several financial metrics, signifying the effectiveness of its risk-return trade-off. By incorporating relevant finance concepts such as Calmar Ratio, VaR, Treynor Ratio, and Information Ratio, the advantages of the peer performance strategy become evident, offering investors the potential for improved risk-adjusted returns.

| Strategy | Calmar Ratio [Annualized] | VaR [Conf. = 95%] (%) | Treynor Ratio [Annualized] | Information Ratio [Annualized] |
|---|---|---|---|---|
| **Panel A: Average Returns Factor** | | | | |
| **Daily** | | | | |
| Benchmark | 0.13 | -11.15 | - | - |
| Peer Performance | 0.43 | -9.25 | 0.50 | 0.63 |
| **Weekly** | | | | |
| Benchmark | 0.02 | -11.15 | - | - |
| Peer Performance | 0.05 | -9.25 | 0.72 | 1.24 |
| **Monthly** | | | | |
| Benchmark | 0.00 | -11.15 | - | - |
| Peer Performance | 0.01 | -9.25 | 0.48 | 0.13 |
| **Panel B: Sharpe Ratio Factor** | | | | |
| **Daily** | | | | |
| Benchmark | -0.45 | -10.25 | - | - |
| Peer Performance | -0.06 | -8.31 | -0.07 | 0.82 |
| **Weekly** | | | | |
| Benchmark | -0.08 | -10.25 | | |
| Peer Performance | -0.01 | -8.31 | 0.06 | 1.09 |
| **Monthly** | | | | |
| Benchmark | -0.02 | -10.25 | - | - |
| Peer Performance | 0.00 | -8.31 | -0.07 | 0.65 |
| **Panel C: M-Sharpe Ratio Factor** | | | | |
| **Daily** | | | | |
| Benchmark | -0.33 | -10.42 | - | - |
| Peer Performance | -0.25 | -8.44 | -0.32 | 0.16 |
| **Weekly** | | | | |
| Benchmark | -0.06 | -10.42 | - | - |
| Peer Performance | -0.04 | -8.44 | -0.05 | 0.04 |
| **Monthly** | | | | |
| Benchmark | -0.01 | -10.42 | - | - |
| Peer Performance | -0.01 | -8.44 | -0.16 | 0.44 |

Table 4.3: Risk-Adjusted Performance Statistics

# Chapter 5

# Conclusion

In conclusion, this thesis presents a comprehensive evaluation of past work on cryptocurrency investment and highlights the effectiveness of the peer performance ratio (Ardia and Boudt (2018)) methodology in the unique and challenging cryptocurrency market. By analyzing the heterogeneity of returns in the cryptocurrency market using three different metrics [Average Returns differential, Sharpe ratio, and Modified Sharpe ratio] at different data granularity levels using screening plots, this study confirms the existence of heterogeneity of returns and the ability of peer performance methodology to capture the outperformance of cryptocurrencies.

Investment strategies using rolling window investments on 53 cryptocurrency trading data from 2017 to 2021 were implemented, considering trailing 1-year daily returns for evaluating the three metrics and their corresponding peer performance ratios. The top 10 percent of cryptocurrencies were selected for investment with daily, weekly, and monthly rebalancing frequencies, and the out-of-sample returns were recorded and analyzed using various return metrics.

The Sharpe Ratio Factor strategy consistently outperforms across all frequencies, while the Average Returns Factor and M-Sharpe Ratio Factor strategies demonstrate mixed results. The analysis of drawdown statistics and risk-adjusted performance metrics, such as the Calmar Ratio, Value at Risk (VaR), Treynor Ratio, and Information Ratio, further validate the superiority of the peer performance investment strategy over the benchmark strategies.

Future research could expand on this study by considering a larger dataset of cryptocurrencies, examining the effects of transaction costs and slippage on the performance of the strategies, and incorporating alternative risk measures and performance evaluation techniques. Additionally, it would be beneficial to explore the impact of changing sentiment and technology in the cryptocurrency market, such as the shift from proof-of-work to proof-of-stake consensus mechanisms, which could potentially influence the market dynamics and volatility. Moreover, the fall of major centralized exchanges like FTX could lead to increased uncertainty and instability in the industry, warranting further investigation into how these developments affect the effectiveness of peer performance ratios and investment strategies.

This thesis contributes to the existing literature on cryptocurrency investment and provides valuable insights for investors seeking improved risk-adjusted returns in this rapidly evolving market. By incorporating the changing landscape of the cryptocurrency industry, future research could further enhance our understanding of optimal investment strategies and risk management techniques in this dynamic and complex domain.

# References


Akcora, C.G., Li, Y., Gel, Y., Kantarcioglu, M., 2018. Bitcoin risk modeling with blockchain graphs. Economics Letters 173, 138–142.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Ardia, D., Bluteau, K., Boudt, K., Inghelbrecht, K., 2022. Climate change concerns and the performance of green vs. brown stocks. Management Science 0.

Ardia, D., Boudt, K., 2018. The peer performance ratios of hedge funds. Journal of Banking & Finance 87, 351–368.

Ardia, D., Boudt, K., Haned, H., Gagnon-Fleury, J.P., 2021. PeerPerformance: Luck-Corrected Peer Performance Analysis in R. URL: `https://CRAN.R-project.org/package=PeerPerformance`. r package version 0.2.4.

Asness, C.S., Frazzini, A., Pedersen, L.H., 2014. Quality minus junk. Available at SSRN 2312432 .

Bali, T.G., Demirtas, K.O., Levy, H., 2009. A time-series approach to option pricing: Models, estimation, and empirical performance. The Journal of Finance 64, 943–983.

Barras, L., Scaillet, O., Wermers, R., 2010. False discoveries in mutual fund performance: Measuring luck in estimated alphas. Journal of Finance 65, 179–216.

Blau, B.M., Ehrlich, S., Lippman, M.A., 2018. Price discovery on bitcoin exchanges. Journal of International Financial Markets, Institutions and Money 52, 190–202.

Bouri, E., Azzi, G., Dyhrberg, A.H., 2017. Is bitcoin a better safe-haven investment than gold and commodities? International Review of Financial Analysis 49, 266–279.

Bouri, E., Gupta, R., Roubaud, D., Wang, S., 2019. Co-explosivity in the cryptocurrency market. Finance Research Letters 29, 178–183.

Brière, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: Portfolio diversification with bitcoin. Journal of Asset Management 16, 365–373.

Caporale, G.M., Plastun, A., Urquhart, A., 2018. Time-varying efficiency of cryptocurrency markets. Finance Research Letters 29, 321–325.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

CoinMarketCap, 2023. Cryptocurrency market capitalizations. `https://coinmarketcap.com/`.

Corbet, S., Lucey, B.M., Yarovaya, L., 2018. Cryptocurrencies as a financial asset: A systematic analysis. International Review of Financial Analysis 62, 182–199.

Croman, K., Decker, C., Eyal, I., Gencer, A.E., Juels, A., Kosba, A., Miller, A., Saxena, P., Shi, E., Sirer, E.G., 2016. On scaling decentralized blockchains, in: International Conference on Financial Cryptography and Data Security, Springer. 106–125.

Elendner, H., Trimborn, S., Ong, B., Lee, T.M., 2016. The cross-section of crypto-currencies as financial assets: An overview. Available at SSRN 2744811 .

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Favre, L., Galeano, J.A., 2002. Mean-modified value-at-risk optimization with hedge funds. Journal of Alternative Investments 5, 21–25.

Fung, W., Hsieh, D.A., 2004. The empirical performance of alternative investments: An update. Financial Analysts Journal 60, 58–81.

Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. Economics Letters 164, 109–111.

Goodwin, T.H., 1998. The information ratio. Financial Analysts Journal 54, 34–43.

Griffin, J.M., Shams, A., 2020. Is bitcoin really untethered? Journal of Finance 75, 1913–1964.

Grinold, R.C., 1989. Performance measurement without benchmarks: An examination of mutual fund returns. Journal of Business 62, 47–68.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jorion, P., 2000. Value at Risk: The New Benchmark for Managing Financial Risk. McGraw-Hill.

LaBonte, B., Rice, E., 2019. Regulating cryptocurrencies: Assessing market reactions to regulatory news. Journal of Corporate Finance 58, 16–29.

Ledoit, O., Wolf, M., 2008. Robust risk measurement and portfolio optimization. Review of Financial Studies 22, 3299–3349.

Liu, Y., Tsyvinski, A., 2018a. Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. Journal of Monetary Economics 109, 245–258.

Liu, Y., Tsyvinski, A., 2018b. An empirical analysis of liquidity and order flow in the cryptocurrency market. Available at SSRN 3182119 .

Lo, A.W., 2002. The statistical properties of hedge fund index returns and their implications for investors. Journal of Alternative Investments 5, 27–44.

Markowitz, H., 1952. Portfolio selection. Journal of Finance 7, 77–91.

Martin, P.W., 1987. The Ulcer Index: A New Way to Rate Mutual Funds. Owl Books.

Momtaz, P.P., 2020a. Initial coin offerings. Journal of Finance 75, 1019–1045.

Momtaz, P.P., 2020b. The pricing and performance of cryptocurrency. European Journal of Finance 26, 409–428.

Moore, T., Christin, N., 2013. Beware the middleman: Empirical analysis of bitcoin-exchange risk. Lecture Notes in Computer Science 7859, 25–33.

Mora, C., Rollins, R.L., Taladay, K., Kantar, M.B., Chock, M., Shimada, M., Franklin, E.C., 2018. Bitcoin emissions alone could push global warming above 2°c. Nature Climate Change 8, 931–933.

Nadarajah, S., Chu, J., 2017. Are cryptocurrencies a safe haven for equity markets? an international perspective from the covid-19 pandemic. Research in International Business and Finance 54, 101248.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Decentralized business review , 21260.

Peterson, B.G., Carl, P., 2020. PerformanceAnalytics: Econometric Tools for Performance and Risk Analysis. URL: `https://CRAN.R-project.org/package=PerformanceAnalytics`. r package version 2.0.4.

Phillip, A., Chan, J., Peiris, S., 2018. Cryptocurrencies as an asset class: An empirical assessment. Finance Research Letters 29, 246–251.

Ľuboš Pástor, Stambaugh, R.F., 2002. Mutual fund performance and seemingly unrelated assets. Journal of Financial Economics 63, 315–349.

Sharpe, W.F., 1966. Mutual fund performance. Journal of Business , 119–138.

Sharpe, W.F., 1992. Asset allocation: Management style and performance measurement. Journal of Portfolio Management 18, 7–19.

Sortino, F.A., 1991. The sortino framework for constructing portfolios. The Sortino Framework for Constructing Portfolios , 199–215.

Sortino, F.A., Price, L.N., 1994. Performance measurement in a downside risk framework. Journal of Investing 3, 59–64.

Stoll, C., KlaaBen, L., Gallersdörfer, U., 2019. The carbon footprint of bitcoin. SSRN Electronic Journal , 1647–1661.

Storey, J.D., 2002. A direct approach to false discovery rates. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 64, 479–498.

Treynor, J.L., 1965. How to rate management of investment funds. Harvard Business Review 43, 63–75.

Treynor, J.L., Black, F., 1973. How to use security analysis to improve portfolio selection. Journal of Business 46, 66–86.

Trimborn, S., Wolfgang KH, H., 2019. Investing with cryptocurrencies-a liquidity constrained investment approach. Journal of Asset Management 20, 110–125.

Urquhart, A., 2016. The inefficiency of bitcoin. Economics Letters 148, 80–82.

Xu, J., Livshits, B., 2018. The economics of cryptocurrency pump and dump schemes, in: Proceedings of the 2nd ACM Conference on Advances in Financial Technologies, ACM. 1–21.

Young, M.R., 1991. Calmar ratio: A smoother tool. Futures 20, 40.