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T.C.
BAHCESEHIR UNIVERSITY
GRADUATE SCHOOL OF EDUCATION
THE DEPARTMENT OF INDUSTRIAL ENGINEERING

A HOLISTIC APPROACH TO MUTUAL FUND PERFORMANCE
RATING: A CASE STUDY IN THE TURKISH MARKET

MASTER'S THESIS

NUR ASENA GÜN

ISTANBUL 2023

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ABSTRACT

A HOLISTIC APPROACH TO MUTUAL FUND PERFORMANCE RATING: A CASE STUDY IN THE TURKISH MARKET

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Industrial Engineering Masters Program

Thesis Advisor: Yaman Ömer Erzurumlu

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The mutual fund market in Turkey, exceeding 1 trillion Turkish Liras and involving over 3.7 million[MYP2][NAG3] investors, presents a complex landscape for non-specialists. Existing ranking methodologies lack holistic perspectives and standardization, making informed investment difficult. This study proposes a comprehensive approach to rating mutual fund performance in the Turkish market. By combining financial ratio analysis, entropy method, and the Simple Additive Weighting methodology, we developed a rating system that considers 70 performance criteria. Using a Python program, we automated performance ratio calculations, improving fund rating accessibility for investors. We tested our approach on historical data, comparing our top-rated fund returns with benchmarks like Gold, USD, EUR, and BIST30. The results suggest our system provides more stable growth, mitigates violent market fluctuation risks, and improves investment guidance in the Turkish mutual fund market. This work can contribute to Turkey's financial sector stability and robustness by fostering informed investment and market growth. Further research may refine this model and apply it to other markets.

Keywords: Mutual Fund Performance Rating, Financial Ratios, Entropy Method, Simple Additive Weighting, Investment Scenarios, Turkish Mutual Fund Market.

ÖZ

YATIRIM FONLARININ PERFORMANSININ DERECELENDİRMESİNE BÜTÜNSEL BİR YAKLAŞIM: TÜRKİYE PAZARINDA BİR VAKA ÇALIŞMASI

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Türkiye'deki karşılıklı fon piyasası, 1 trilyon Türk Lirasını aşan bir değer ve 3.7 milyondan fazla yatırımcı ile yatırımcılara karmaşık bir manzara sunmaktadır. Mevcut sıralama metodolojileri, bütüncül bakış açılarından ve standartlaşmadan yoksun olup, bilinçli yatırımı zorlaştırmaktadır. Bu çalışma, Türk piyasasında karşılıklı fon performansını değerlendirmek için kapsamlı bir yaklaşım önermektedir. Finansal oran analizi, entropi metodu ve basit ekleme ağırlıklandırma metodolojisinin birleştirilmesiyle, 70 performans kriterini dikkate alan bir derecelendirme sistemi geliştirdik. Bu süreçte bir Python programı geliştirdik böylece performans oranı hesaplamalarını otomatikleştirdik, bu da yatırımcılar için fon derecelendirmesinin erişilebilirliğini artırdı. Yaklaşımımızı tarihi verilere uyguladık ve en iyi dereceli fon getirilerimizi Altın, USD, EUR ve BIST30 gibi referansları ile karşılaştırdık. Sonuçlar, sistemimizin daha stabil büyüme sağladığını, şiddetli piyasa dalgalanma risklerini azalttığını ve Türk karşılıklı fon piyasasındaki yatırım yönlendirmesini iyileştirdiğini göstermektedir. Bu çalışma, bilinçli yatırımı ve piyasa büyümesini teşvik ederek Türkiye'nin finansal sektörünün istikrarına ve sağlamlığına katkıda bulunabilir. Daha ileri araştırmalar bu modeli rafine edebilir ve diğer piyasalara uygulayabilir.

Anahtar Kelimeler: Yatırım Fonlarının Performansının Derecelendirmesi, Finansal Oranlar, Entropi Yöntemi, Basit Toplam Ağırlıklandırma, Yatırım Senaryoları, Türkiye Yatırım Fon Piyasası.





To My Mother

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[MYP4]

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LIST OF ABBREVIATIONS

MF	Mutual Fund
TRY	Turkish Lira
SDI	Strategic Distinctiveness Index
ETF	Exchange Traded funds
CDs	Certificates of Deposits
Repo	Repurchase Agreements
BAs	Bankers' Acceptance
DJIA	Dow Jones Industrial Average
SAW	Simple Additive Weighting
SAHA	SAHA Corporate Governance and Credit Rating Services
LUDENS	LUDENS Advanced Financial Services and Consulting Ltd. Sti.

Introduction

Chapter 1

The mutual fund market in Turkey is progressively expanding. Even if we only look at Umbrella Mutual Funds there are 511 active Mutual Funds with a market capitalization of 343 billion Turkish Liras (TL), the diversity and sheer number of options can be both enticing and overwhelming for investors. This wide-ranging financial ecosystem is composed of various types of Mutual Funds. Leading the pack are Free Umbrella Mutual Funds (MF) with 121 funds, closely followed by Changeable Umbrella MFs with 98 and Stock Umbrella MF with 93. These three major players collectively amass a market capital of over 209 billion TL, highlighting the significant financial role they play in the Turkish economy (TEFAS İstatistiki Raporlar, 2021).

The allure of mutual funds has broadened its appeal beyond companies and extended to everyday individuals. Mutual funds offer numerous benefits to their investors, such as low commission fees, tax advantages, and professional portfolio management. However, despite these benefits, the complexity of understanding and utilizing various financial ratios that rate mutual funds becomes a significant barrier to many potential investors. The prevalent issue of people making ill-informed investment decisions or being discouraged from investing at all due to a lack of comprehension creates a ripple effect that adversely impacts both the individual investors and the broader market.

Existing companies that provide ratings for MFs often fall short in their approach. They may base their ratings on risk, performance, or other criteria but seldom adopt a comprehensive, holistic perspective. This piecemeal approach often leaves investors making decisions based on a single or faulty criterion. The consequence of this practice is a tendency for individual investors to lean towards investing in their trusted fund type, inadvertently creating market bias and impeding growth and stability.

Our study aims to address these prevalent issues by proposing a novel, holistic approach to rate mutual funds. By integrating a combination of methodologies, we aspire to provide an all-encompassing rating system. Firstly, we created a Python

program to automate the calculation of up to 70 different financial ratios for each mutual fund. The use of a custom-made Python program eliminates human error and increases efficiency in handling the large amount of data. This program stands as the first step in our methodology, providing a foundation for further analysis.

The subsequent step employs the Entropy multi-attribute decision-making method. This method is used to rank the funds based on their calculated ratios. It assigns an unbiased, objective weight to all the financial ratios by factoring in all performance indicators and their results without overlooking any data.

Finally, we implement the Simple Additive Weighting (SAW) method to consolidate the ranks obtained from the Entropy method into a final, comprehensive rating. This composite rating generated by our system offers a more reliable and holistic evaluation of the mutual funds.

As we delve into this complex world of mutual funds, it's essential to keep in mind that the global fund market is growing steadily. Notwithstanding the challenges and difficulties, the worldwide investment of funds has seen a substantial increase. This growth can be seen from the 4.7% increase in worldwide investment of funds in 2021, and upon closer look United States and Europe's investment market also grew respectively by 5.4% and 4.4%. Specifically, in Turkey, the fund market experienced growth by 2.8%, with the fund capital escalating from 3.15 billion TRY to 8.96 billion TRY within a span of one year in 2021 (EFAMA European Fund and Asset Management Association, 2021).

Through our research, we aspire to offer a comprehensive tool for investors to make informed decisions and for the market to achieve its full potential, eventually fostering a healthier financial ecosystem.

Scale and scope of the study: This research investigates the performance of various types of mutual funds in different markets. We analyzed a select number of performance criteria within a specified time frame. Our analysis includes 1122 different Mutual Fund types in the Turkish market. We developed a Python program to automatically calculate the performance ratios and used Entropy decision making methodology to assign weights each performance criteria and finally we created a comprehensive rating methodology by using the Simple Additive Weighting (SAW) method to rank the different types of mutual funds. We then conducted portfolio

simulations using the calculated ratings to compare the performance of different investment strategies. Our analysis covers the period from 01.02.2020 to 01.02.2022. Please note that our simulation results should be interpreted within the context of our study's scale and scope, considering the limitations and assumptions made.

Literature Review

Chapter 2

2.1 Mutual Funds

A Mutual Fund is a type of financial tool that collects money from multitude of investors and invests this money into various financial market securities such as bonds, stocks, money market instruments and other financial assets. For the mutual fund the sum of these investments are called the Mutual Fund's Portfolio. When the investors invest money into these portfolios, they own shares of the mutual fund. These shares then serve as the investor's slice of ownership in the mutual fund and its generated income. Mutual funds need professionals to operate their investment decisions, these people are then called money managers or fund managers. Mutual funds have a written promise with their investors in which topics such as the investment objectives are given which is called the prospectus of the mutual fund. The fund managers are obligated to uphold to the standards of the prospectus as this is the reason that investors have chosen to invest in the mutual fund in the first place.

One of the biggest benefits of mutual funds are that, they allow everyday people to invest in money market instrument that are normally unreachable for them. Mutual funds give these investors entrance to diverse portfolios that are professionally managed. By buying a part of the mutual fund these investors share in the gain or loss proportional to their investments.

When it comes to the success or failure of the mutual fund, the total change in the market capital is usually taken as an indicator. This market capital is calculated by the average performance of the different money market instruments that the fund has invested. So, in the end the, the value of the mutual fund lies in the success of the

securities that the portfolio managers have chosen to invest. Furthermore, in a usual mutual fund, the fund managers take the investments that the shareholders have invested and invest those capital to different securities that they think will bring gain to the overall portfolio. In that sense, mutual funds usually have annual fees (which are also known as expense ratios) that both compensates the management of the portfolio and brings in new capital to invest more in securities. So, when an investor decides to buy a mutual funds' unit or share, the investor is actually choosing buy the portfolios performance, or to be more precise part of the value of the portfolio.

Mutual Funds can be divided into numerous different categories and types according to their investment decisions. These categories represent which kind of securities that the fund invest in, what are the funds' objective and what kind of return the portfolio seeks. In the next part the different kinds of mutual funds are explained in more detail.

2.2 Mutual Fund Types

2.2.1 Equity funds. Equity funds make up the largest category, as most of the mutual funds belong in this category. Equity funds invest in equities by buying stocks of different publicly traded companies. Equity funds are more likely for growth however they are more volatile and riskier in terms of value. Equity funds are also divided into subgroups according to their investments. Some examples to these subgroups are as follows:

- *Mutual funds the invest based on company size:* Some mutual funds choose to invest only in “large scale” or “small scale” companies, these scales refer to the value or market capitalization of the company. Small scale (also known as small-cap funds) funds, usually choose to invest on companies that have a worth of \$300 million to \$2 billion, middle scale (also known as mid-cap funds) funds, usually choose to invest in companies that have a worth of \$2 billion to \$10 billion and finally large scale (also known as large-

cap funds) funds, usually choose to invest in companies that have a worth of \$10 billion or greater.

- *Sector or Industry Funds:* As the name suggests these funds invest in a particular sector or industry. As sectors widely differ, there is a vast amount of different sector or industry funds. For example, an equity fund that chooses to invest only in the health industry becomes a health fund. However, these mutual funds carry a high risk because all of their investment lies in a singular sector and if that sector crashes all the securities in the mutual fund will face losses. So, it is always better for investors to invest in several different sector or industry funds.
- *Value and Growth funds:* These funds carry a different strategy while investing. For Value Funds, portfolio managers look for stocks that are undervalued by the market, as for Growth Funds portfolio managers look for stocks that they believe will gain more value and will have a higher return than the average stock.
- *Global, International and Emerging Markets Funds:* Building mutual fund portfolios are also related with the geographic locations. International funds focus on investing in funds or companies that are outside of the origin of the location of the portfolio managers. On the other hand, global fund portfolio managers invest in securities both in their home country and also outside of their home country. Emerging market fund portfolio managers choose to invest in securities from countries whose market value they expect to grow.

2.2.2 Fixed income funds. In Fixed Income Funds, portfolio managers make investment decisions that will bring the shareholders a return on preset intervals. The main goal is to achieve developing interest from securities and then passing these on to the shareholders. This kind of mutual fund is also called bond funds as they mostly invest in bonds because of their returns. Fixed Income Fund portfolio managers perform a more hands on management policy and actively pursue undervalued bonds that will bring back a higher return for their shareholders. Some of the investment options for Fixed Income Funds:

- Treasury Bonds
- Corporate Bonds
- Treasury Bills
- Treasury Notes
- Municipal Bonds and etc.

2.2.3 Index funds. The idea behind index mutual funds lies in the belief that it is almost impossible and very expensive to be constantly better than the investment market. To overcome this an index fund portfolio manager invests in stock which are in a dominant market index such as *Dow Jones Industrial Average (DJIA)* or *S&P 500*. Index fund approach also needs much less the management and analyzation which allows for a passive investment strategy. Thus, as there are fewer expenses the returns directly goes to the shareholders in a higher value. Index funds are in general advised to be ideal as retirement funds as they are long term investments. As index funds aim to line up with the return and risk of the market, it is theorized that eventually the market will surpass all the single investments and bring return to its investors. Some well-known market indexes are as follows:

- *MSCI EAFE*: it is made up of stocks from Europe region, Australasia region and the Far East.

- *Nasdaq Composite*: This index focuses on Nasdaq exchange list and the 3000 stocks that are listed on there.
- *Russell 2000*: focuses more on small capital companies and their stocks.
- *Bloomberg Barclays US Aggregate Bond Index*: this encompasses all the bonds in the US market

2.2.4 Balanced funds (Hybrid Funds). Balanced mutual funds also known as Hybrid Mutual Funds have a diversification strategy when it comes to investment. Portfolio managers of these funds allocate the investment decision toward different investment tools such as bonds, stock and any other money market instruments. The overall aim with this strategy is to reduce the overall risk by investing in different classes of assets. This is why they are also sometimes called asset allocation funds. They are two different strategies when it comes to balanced funds. The first one is a set strategy for allocation which is fixed and written in the prospectus. This way the shareholders can have a foreseen exposure to different classes of assets. The second strategy is more dynamic to encounter the objectives of various shareholders. In this strategy the portfolio manager responds accordingly to phenomenon such as changes in business cycles, market conditions or even the changes to the investors' life cycles. Thus, balanced mutual funds take on less risk than that of equity mutual funds.

2.2.5 Money market funds. Money Market Mutual Funds are low risk investment options that focus on short term securities. Usually these funds focus on government treasury bills however they can also invest in highly rated debt-based investment options or cash equivalent securities. In these kinds of funds, the shareholders won't lose their principal investments, but the fund will not bring a high return. Usually, the shareholders get slightly more return than their investments. So, in the long run money market mutual funds are not suitable for long-term investment options and should be considered for temporary cash holding. Some options of investment for money market funds:

- Treasuries
- Certificates of Deposits (CDs)
- Repurchase Agreements (Repo)
- Bankers' Acceptance (BAs)
- Commercial Papers

2.2.6 Income funds. Income Funds, also known as Exchange-Traded funds (ETF), focus on generating an income to their investors whether it be yearly, monthly or quarterly. This income is given to the investors usually in the form of dividend payouts or interest. Instead of capital gains they focus on managing a steady income stream. These funds generally invest in government securities, high rated corporate debt instruments or stocks that pay dividends. The idea is that the portfolio manager holds these securities until they are mature and then sells them to provide income to the shareholders. As such they are usually considered to be lower risk, than the general mutual fund types.

2.2.7 Specialty funds. Specialty Mutual funds can be defined more as a wide-ranging fund type where all the popular but hard to categorized funds are placed within. The funds inside of here choose to focus on topics such as a specific area, sector, category or industry. So instead of diversification they choose to fixate on a definite area of the economy or a predetermined strategy. However, they can be considered as volatile because when focusing, for example on a single sector, they carry the risk of the sector crashing. This would mean that as all the invested securities were in the same sector, the fund and the shareholder would face a loss. Because of this fact specialty mutual funds are generally considered as high risk. However, on the other hand, some of the specialty funds carry the possibility of a high return on the long run. An example of a specialty mutual fund is as follows:

- *Socially Responsible Funds:* These kinds of fund are also called ethical funds. The portfolio managers of these funds choose to invest in companies that take into account ethical beliefs and guidelines. The idea behind these kinds of funds is to maintain a return while still maintaining the sense of right or wrong.
- *Gold Mutual Funds:* A Gold MF purchases assets that are in relation to gold and other valuable precious metals. These funds have to have %80 of its assets as a gold derivative. The top three variances in gold MFs are, the MFs that invest in actual gold, MFs that invest in gold related companies and gold contracts. Usually people who want to fight against inflation choose to invest in gold funds.
- *Commodity Mutual Funds:* Commodity MFs invest in commodities which are raw materials, raw agricultural goods and precious metals such as gold and silver. Furthermore, commodity MF can invest in different

sectors such as energy where they invest in gas and oil or agriculture where they invest in raw materials such as wheat.

- *Foreign Exchange Mutual Funds:* Foreign Exchange MFs are funds that have at least 80% of their assets as currency or currency-based assets. These funds aim to bring a high return on the medium and long run by investing in currencies.
- *Foreign Mutual Fund:* Foreign MFs choose to invest in companies that are either international or based outside of the funds home country. Thus, these funds are also called *International Mutual Funds*. Foreign MFs are seen as more volatile as they bring in risk with problems such as different economies, issues between countries and the changes currency.
- *Participation Mutual Fund:* Also known as Participation Umbrella funds always consists of assets such as participation accounts, lease certificates, partnership shares, gold and other precious metals, and different not interest-based money and capital market assets which are approved by the Board (TEFAS İstatistiki Raporlar, 2021).

2.2.8 Umbrella mutual funds. An umbrella fund is essentially a collective investment scheme that exists as a single legal entity but has several distinct sub-funds or portfolios. Each of these sub-funds operates as an individual mutual fund, but they are all part of the larger umbrella structure.

One of the main benefits of umbrella funds is that they allow investors to diversify their investments across various sub-funds while dealing with only a single fund. This simplifies the process for the investor as they do not need to manage multiple fund accounts. Additionally, umbrella funds can offer economies of scale, as the

costs of running the fund can be distributed across the different sub-funds, potentially leading to lower fees for investors.

2.3 Mutual Funds Advantages and Disadvantages

Mutual funds can be considered as one of the most favored investment tools for a great number of investors. However, before investment the advantages and disadvantages of mutual funds should also be discussed. In that sense first advantages of the mutual funds will be discussed.

2.3.1 Advantages of mutual funds. There are a vast number of reasons to why a great number of investors choose to invest in Mutual Funds. Apart from being one of the most used investment tools, Mutual Funds are vastly used as retirement investments both by individuals but also by employers. Below some advantages of mutual funds will be discussed.

- *Economies of scale:* Investors of mutual funds also save money by economies of scale. By purchasing a share of a mutual fund, they overcome the charges of buying multiple securities with one mutual fund. If the investors have chosen instead to buy every single security under the mutual fund, they would have faced a large transaction fee. Furthermore, the usual investment price of mutual funds are much lower than usual securities, so more people are able to invest in mutual funds.
- *Diversification and risk reduction:* One of the main advantages of mutual funds lies in the fact that it is usually diversified. Most of the time portfolio managers create a diversified portfolio that includes different kinds of assets to reduce risk. By investing in different kinds of securities,

the portfolio managers make sure that losses are minimized and returns are maximized.

- *Easy access and fair pricing:* As they are usually traded in the biggest stock exchange markets mutual funds are very easy to buy and sell which makes them remarkably liquefiable assets. They are also fairly simple to understand and generally have lower than average minimum investment rates.
- *Professional Portfolio Management:* Mutual funds are managed by professional portfolio managers that are paid through management fees. These fees are usually quite low, and the benefit of professional management overcomes the loss of this fee. Portfolio managers commonly stick to the prospectus of the mutual fund; thus the investors always know how their investments are managed.

2.3.2 Disadvantages of mutual funds. While Mutual Funds are quite beneficial investment tools, there are still some problems that might occur during the investment period. Some of these problems will be mentioned below:

- *Mismanagement from managers:* Some portfolio managers may abuse their power over the investment and conceal the real values and ratios from the investors. Portfolio managers might also make bad investment decisions and lead the investors to great loss.
- *Excessive pricing and high fees:* The cost of the portfolio managers are paid by investors with timed intervals. Some mutual funds take advantage of this fact by putting high expense ratios or by putting overpriced management fees. Investors sometimes doesn't even understand what they are

agreeing with the expense ratios as they don't read the prospectus and this leads to portfolio managers abusing their power to extort more money from investors.

- *Results not guaranteed:* For most of the mutual fund types, the results are not guaranteed. When the share is sold it could be the same as the initial amount, less than the initial investment or more than the investment. These are related to the market conditions and they rely on the ability of the portfolio manager.
- *No control given to the investors:* After buying a share of investment, shareholders have no say over the holdings of investment. The investors have no decision power other than selling and buying the shares of the funds.
- *Exit load:* When shareholders want to sell their shares and therefore exit the mutual fund before a specific time period, some funds charge penalty fees called exit loads. This amount changes from fund to fund however some have hefty amounts according to the initial investment of the shareholder. The time periods and exit loads are written in the prospectus and usually no special allowances are given.

2.4 Fund Performance

Fund performance have been mentioned quite a lot in the literature. When going back through the literature, the evolution of fund performance and its evaluation criteria can be divided into six generations. There are many opinions and reviews about the best methods and criteria to use in fund performance evaluation, however there is no concrete evidence to support a single or multiple best performance evaluation method. In the following sections, the evaluation of fund performance analysis techniques will be discusses.

Sharpe and Treynor are the founding fathers of the first generation of fund performance analysis techniques. In his studies Sharpe focused on creating criterion to diversify the traditional analysis techniques (W.F., 1966) and on the other hand Treynor focused on regression analysis which focuses on abnormal returns (Treynor J.L., 1965). There are other researches in the first generation such as the average variance (Harry, 1952) which is the elementary block of diversification and performance criterions based on Capital Asset Pricing Model (CAPM) (Roll, 1978) (R., 1977) however these were heavily criticized on structural and economical basis. Still to this day, models are created for fund performance which only focuses on one aspect or limited number of factors. Most of the research or studies are done by combining a limited number of different ratios and mathematical models and creating new systems with these criterions. This means that when analyzing the performance of funds there is a very limited range of criterion that goes into play and this means all the available performance analysis techniques are lacking in different aspects.

The second generation of fund performance analysis generally focuses on average-variance. In this case the main problem of the investor is the relationship between risk and return. However different researches show that there are many factors and criteria that are both qualitative and quantitative that impact this relation. Thus, only using risk to assess performance does not allow a comprehensive analysis of performance. Even Morningstar rating which is globally excepted have been found lacking in that aspect (Lisi & Caporin, 2012). Even Morningstar emphasizes that their performance rating systems are a tool for pre-decision making and that their users should analyze the fund that fits them the most more carefully before making a decision. Morningstar rating system compounds in 3 main sectors and 11 sub sectors that are geographically categorized. In the rating system these sectors have various investment tools that are rated according to different risk preferences (Kahneman, Knetsch, & Thaler, 1991) and then categorized again by rating them according to the expected biggest benefit to the least (Bernoulli, 1954) and the highest score gets the best rating. However even when we accept that the risk oriented approach is better than the other options, we cannot give a definite answer as to which criteria measures the risk the most correctly (Babalos, Caporole, & al., Testing the Persistence in Mutual Fund Performance and the ex-post verification problem: evidence from the Greek market, 2008).

For the third generation of mutual fund performance analysis the main methodology was to compare the second-best investment option to the best investment option to evaluate the value created by the fund manager (Berk & Binsbergen, 2012). The main idea behind this was apart from the most used measurement factors such as risk and return, to measure the human factor that made the decisions of sell, hold and buy and measure the impact it made on the overall success of a mutual fund. So, measure of performance carries a great importance for both fund type and the active management of the fund. Furthermore, this is cemented by the fact that investors who actively manage their portfolio have a greater return than that of investors who adapt a passive management approach (Narayan & Suhas, 2017) which leads to the importance of correct measurement of general performance and selecting correct fund options. From the beginning of modern financial research whether if the fund managers have the necessary qualifications to manage portfolios have been argued (Jensen M. C., 1968). From the first studies of Treynor (Treynor J. , 1965) and Sharpe (Sharpe, 1966), to more current studies such as Gruber (Gruber, 1996) and Carhart (Carhart, On persistence in mutual fund performance, 1997) and to even more recent studies of Fama & French (Returns, 2010), the literature shows that actively managed funds do not over perform their benchmark passive managed funds. Because of the fact that rating systems are highly used by the investors and the fact that funds' asset flow is changeable according to the fund rating, the methodologies that are used in the rating systems carry a great importance (Muller & Weber, Evaluating the Rating Stiftung Warentest: How good are mutual fund ratings and can they be improved?, 2014).

So, to this extend the fourth generation of mutual fund performance analysis system have been generated. This generation focused on evaluating market timing and investment tool choosing qualifications. The frontiers of this generation were the models of Treynor & Mazuy (Treynor & Mazuy, 1966), Jensen (Jensen M. , 1968) and Henriksson & Merton (Henriksson & Merton, On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills, 1981). The main idea of this generation of performance evaluation was whether if the portfolio managers who possessed these skills were rewarded by the market or not. The findings were that the portfolio managers were indeed not rewarded. This finding which is against the ature of finance showed that even if the managers did not

show these particular skillsets they still got a return on the overall added value (Berk & Binsbergen, 2012). However in more recent time, for example Kosowski (Kosowski, 2006), Cheng & Yan (Cheng & Cheng, 2017) and Blake et al. (Blake, 2017) with the bootstrap method and Baks et al. (Baks, Metrick, & Wachter, 2001) and Pastor & Stambaugh (Pastor & Stambaugh, 2002) with their Bayesian approach found out in their studies that some fund managers have a positive alpha value which is important to notice for lasting performance in terms of investors. However, it is not realistic to rely on the techniques that puts the fund performance in any single factor (Barras, Scaillet, & Wermers, 2010). Thus, the detection of lasting performance in terms of funds gained more importance.

The fifth generation of mutual fund performance analysis focused on the examination of positive lasting fund performance. Grinblatt & Titman (Grinblatt & Titman, 1992), Hendrics et al. (Hendrics, Patel, & Zeckhauser, 1993), Goetzmann & Ibbotson (Goetzmann & Ibbotson, 1994) and Cremes & Petajisto (Cremers & Petajisto, 2009) in their studies showed that positive performance is lasting, however on the other hand Jensen (Jensen M. C., 1968) and Malkiel (Malkiel, 1995) and Carhart (Carhart, 1997) on the USA funds and Babalos & Carpole (Babalos, Caporale, & et.al., 2008) et al on Greek funds found out in their studies that performance is not lasting. Furthermore, many different studies showed that short term lasting performance have been more evident (Grinblatt & Titman, 1992) (Hendrics, Patel, & Zeckhauser, 1993) (Goetzmann & Ibbotson, 1994) (Carhart, 1997).

The final performance measurement analysis group consists of studies that focus on timing skills of fund managers. These studies under this title has been started by Henriksson & Merton (1981), and they have started a new performance evaluation group with a new perspective (Ferson & Schadt, 1996) (Ferson & Warther, 1996) (Christopherson, Ferson, & Glassman, 1998). The most important features of the study are that it allows for expected return and risk measures that change over time. In the condition that determined time rules are followed the study is not below a passive portfolio is proved by Bollen & Busse (2001) and that there is an additional added value is proved by Hammami & Oueslati (2017).

Performance evaluation is important both in terms of active fund management and fund category. The fact that the investors who actively manage their funds gain

more return than that of passive investors brings more importance to the fact of correct evaluation of performance and the correct selection of fund (Narayan & Suhas , 2017). The fact that rating systems are used frequently by the investors and the asset flow into these funds are changed according to these rankings lead to the conclusion that the methodologies that are used in these ranking systems are of high importance (Guercio & Reuter, 2014) (Muller & Weber , 2014). During the last forty something years there were several different results in the topic, however fund performance evaluation has kept a wide space in the literature (Babalos, Caporale, & et.al., 2008) (Matallin-Saez, Soler-Dominguez, & Tortosa-Ausina, 2014).

Most of the studies have used a combination of limited amount of criteria with multiple variable analysis techniques. With this analysis family there is a limited amount of parameters that could be inputted into the model. As the literature have put forward, the decision that is taken with the usage of not enough input, would be insufficient or highly sensitive to making mistakes because of the fact that they are approaching to performance through a single aspect (Caporin, Jannin, & et.al, 2014) (Kourtis, 2016). The approaches that only take risks or only take ratios into considerations such as Sharpe give out incomplete results (Lisi & Caporin, 2012). Even though there are different techniques that are trying to lessen these mistakes such as Sharpe Ratio Square technique or the fact that Sortino criterion has developed some genetic algorithm models, it is still unclear which measurement tool has been the most effective performance measurement tool, however the results point out that using one criteria leads to errors while measuring performance (Kourtis, 2016) (Cheng & Cheng, 2017) (Caporin, Jannin, & et.al, 2014) (Chen & Huang, 2011).

2.5 Studies Supporting the Lack Of Methods That Do Not Holistically Rate

Mutual Fund Performance:

Guercio & Reuter (Guercio & Reuter, 2014) has deducted that investors are more inclined to invest in funds that have high return and are actively managed however they also found out that after the performance expenses and the commissions were deducted most of the actively managed funds performance was not that much above that of passive indexed funds' performance. Agnesens

(Agnesens, 2013) puts forward that performance ranking systems which are adjusted to classical risk are not objective, and defends that ranking the funds without examining fund characteristics and creating an asset distribution based on active fund managers living area (homebias) and the market capital weight decrease the potential of profit.

Barras et al. (Barras, Scaillet, & Wermers, 2010) during their studies validated that classical tests was insufficient for positive or negative (+/-) alpha determination and thus validated that in the standard tests, the 20% group that fall under the positive indicator, it is not through good management or skills but merely luck that makes them fall under the positive group. Even though positive (+) indicator towards the managers performance, Pool et al. (Pool, Stoffman, & Yonker, 2012) during their studies, found out that especially more prominently in young and inexperienced managers, there is a positive (+) tendency to hold the asset portfolios where they previously have worked, lived or the institutions they previously worked for even though they do not generate a positive (+) return, and subsequently showed that this could make a negative (-) impact on fund managers' performance. Apart from this, Pool at al. (Pool, Stoffman, & Yonker, 2012) also observed that fund managers who have social contact or are physical neighbors have approximately %13 similarities in their asset holdings.

In order to understand how the social structure affects performance Csaszar (Csaszar, 2012) has studied funds that are managed by mutual managers, he tried to understand how the organizational management style affects the fund's performance and in his studies found out that increasing the consensus level decreased the errors that that affected he performance in a negative (-) aspect however it also lead to missing out on opportunities that could have led to positive (+) impact on performance. Clare et al. (Clare & et.al, 2014) between the years 1997 and 2011 in United Kingdom conducted a research using time series data of actively managed mutual funds before fund manager change and after fund manager change and measured performance analysis, thought out this studies they found that when a bad performing fund manager was changed fund performance was evolved towards mediocre however, when a good an high performing fund manager was changed they observed that the fund performance started to regress and have a tendency to incline towards mediocracy, they further explain that this is because when a successful fund

manager leaves their post fund families have trouble filling the vacant position with a new fund manager who is able to keep up the same success.

Huang et al. (Huang, Sialm, & Zhang, 2009) in their studies about risk shifting, found out that various fund managers engage in risk shifting behavior during the investment period and furthermore they also found out that fund manager who manage their portfolios at a fixed risk level overpass the performance level of those managers who make risk shifting in their portfolios. Chen et al. (Chen, Goldstein, & Jiang, 2007) whom conduct studies on portfolio weight and the affect of content changes on performance, demonstrated that while managers implement short term strategies that can affect the liquidity of the fund such as risk shifting, window dressing and etc. they can face liquidity problems and financial fragility when faced with sudden sales and investor exits.

Babalos et al. (Babalos, Doumpos, & et al., 2014), whom emphasizes that there is an increase on researchers for mutual fund performance analysis that focus on processor methods that are parametric or non-parametric, defend that funds that have multiple variety and attribution cannot be evaluated by one performance ranking system, they further defend this by demonstrating that in a study that they have conducted on a mutual fund performance rating with a multiple criteria data envelopment analysis study their results are very similar to that of Morningstar's rating systems' results thus defending that in today's where there are multiple variety funds in the financial markets, single criteria performance ranking systems are insufficient to measure the performance of funds in an efficient manner.

Chen et al. (Chen & et. al., 2011) have compared the fund who are managed by fund families by their fund quarters and other funds whom are managed by third parties by outsourcing systems and found out that fund whom are managed by the headquarters are have shown a higher performance than the funds who are managed by outsourced parties. The fact that the number of funds who are managed by outsourced parties are higher than that of funds that are managed by headquarters and that they show low performance are interpreted as a way of providing convenience for fund family board of management for a way to lead outside through outsourcing the funds which are close to expire. Sun et al. (Sun, Wang, & Zheng, 2010) whom state that commerce strategies that are known by most bring very little return in the end, have created a method that they have called Strategic

Distinctiveness Index (SDI) to create a way for hedge funds to bring higher returns, with this method they tried to evaluate strategically how separate hedge funds are discrete from classical funds in terms of the transactions made. While creating the SDI index a multiple criteria evaluation method is used which takes into context parameters such as the previous profit performance, profit volatility, fund age and size, fund redemption notice period, fund lock up period, fund incentive fee ratio and portfolio asset content. Similar to that study, Chang et al. (Chang & et. al., 2010) also studies evaluating fund performance with multiple criteria decision making methods, in their studies they use multi criteria decision making method where Treynor, Sharpe, Jensen's Alpha and similar commonly used evaluation methods are more prominent to rank 82 funds which are operant on Taiwan market on a 34 month time scale and used Minkowski distance method to rank these fund from good to bad according to their performance.

2.6 Research Supporting the Holistic Rating Of Mutual Fund Performance

Kerstens et al. (Kerstens, Mounir, & Woestyne, 2011) confirms that in investment markets where the product variety and the options are increasing there is an increasing flow towards performance evaluation and measurement with frontier methods which are not based on classical parameters. Angelidis et al. (Angelidis, Giamouridis, & Tessaromatis, 2012) in their studies, they defend that fund performance measurement methods which are intended towards comparison of funds with passive indexes or different risk groups, are erroneous because of the fact that they are not able to determine the fund managers asset decision and timing abilities and that they are not based on comparison of fluid or constant similar risk groups criterion thus they defined the main reason behind the enlargement behind the flow that Kerstens et al. (Kerstens, Mounir, & Woestyne, 2011) have pointed at. Jank (Jank, 2011) who conducts research about aforementioned frontier methods, has put forward that above explaining mutual fund return ratio, variables such as bond yields, changes in real economy and etc. can also explain capital in flow and out flow through the mutual funds and shown that there is a statistical meaningful relationship between capital flow through funds, and stock market return, bond yield

rates and real economy. Stohs et al. (Stohs & et. al., 2015) who also puts forward another frontier method, has examined whether if the most successful funds which are at the top 25% stay successful or not through a one year time period, by basing their studies on the Bernoulli events and came to the conclusion that only a small fragment of the successful funds could stay successful for a long period of time. However, they found that through their studies the reason the funds were not able to stay successful were not because of the fact that the fund management were skillful or unskillful but because of the nature of investment when a successful strategy arises other investors also copy this strategy thus nullify the positive effects bring back the funds to ground zero.

Amihud & Goyenko (Amihud & Goyenko, 2009) has proposed a method that could predict meaningfully whether if a fund's performance would change in a positive (+) or negative (-) aspect in the upcoming periods on a statistical sense, using data such as R2 which is achieved by statistical regression, RMSE and etc. with a mutual fund's idiosyncratic risk, general market risk level and other similar data.

2.7 Mutual Fund Ranking Systems

In this section, the different ranking systems in the world and in Turkey will be discussed. In the first section global mutual fund ranking systems will be discussed.

2.7.1 Global mutual fund ranking systems. In the global fund rating market, the dominant player is Morningstar, Inc., a renowned financial services firm that provides a wide array of investment research and investment management services. One of its most recognized services is the mutual fund rating system. Despite its international presence and recognition, Morningstar's approach to rating mutual funds is not holistic as it does not account for a wide range of financial ratios.

Morningstar's mutual fund rating methodology is primarily based on two systems: the Morningstar Star Rating and the Morningstar Analyst Rating. Both methodologies offer distinctive perspectives on fund performance but do not cover all possible aspects that could potentially impact a fund's future performance.

Morningstar's methodology utilizes specific financial ratios such as return, risk, expense ratio, fund manager tenure, and assets under management. While these ratios offer a significant perspective, they do not encompass a comprehensive range of financial ratios that could provide a broader understanding of a fund's performance.

The Morningstar Star Rating is a quantitative measure that rates funds based on past performance, considering both risk and cost. This rating is retrospective, analyzing a fund's past performance but not necessarily providing a prediction for future potential.

The Morningstar Analyst Rating is a more qualitative measure, reflecting Morningstar analysts' conviction in a fund's ability to outperform its peer group and/or relevant benchmark on a risk-adjusted basis over the long term. While this system considers factors such as the quality of the fund's management and the effectiveness of its investment strategy, it still may not consider all potential variables that could influence a fund's performance (Morningstar, 2021).

Morningstar's approach, despite its wide usage and industry recognition, has received criticism for its heavy reliance on past performance. Critics argue that the star rating system, with its focus

on historical data, may not offer investors a comprehensive tool for future performance prediction. This methodology also lacks the holistic approach and doesn't incorporate a broader range of financial ratios, limiting the depth and diversity of its evaluation.

In conclusion, while Morningstar provides valuable tools for investors to compare funds based on past performance and certain qualitative attributes, its approach does not provide a holistic perspective, thereby creating a need for a more comprehensive mutual fund rating system.

2.7.2 Fund ranking companies in turkey. In Turkey's mutual fund market there are only two companies who dominates the market in terms of ranking the mutual funds which are SAHA Corporate Governance and Credit Rating Services and LUDENS Advanced Financial Services and Consulting Ltd. Sti.. Below, the companies and their methodologies will be explained.

2.7.2.1 Saha corporate governance and credit rating services (SAHA). SAHA in their methodologies aims to merge return and risk in an easy and useful manner to evaluate and rank the mutual funds. Their methodology only considers quantitative values and does not account any subjective evaluation. The evaluation does not put forward any idea about SAHA's opinion about the funds future potential but only considers the funds previous performance in terms of its benchmarks and ranks it according to these evaluations.

Mutual Funds are evaluated at the end of each month in terms of risk and return with benchmarks within their same categories. By rewarding high return and punishing high risk, SAHA ranking systems aims to push forward mutual funds who have more reasonable risk levels and good return opportunities. The rating and the start allocation is done monthly on "monthly", "yearly" and "3 years" basis. The reason the ranking is divided into different time periods is to give the investor a real perspective of how the mutual fund is performing on short, middle, and long-term periods. The mutual funds that are on the ranking

systems are the ones that the public listings have passed for at least for one years.

SAHA's ranking methodology is based on five performance measures:

- *Performance (return) measurement*; this criterion measures the monthly (yearly, 3 years) % return of mutual fund unit price. For measuring the % for each month, the last working day unit price of the month and the previous months last working day units' price; for measuring the % for each year, the last working day unit price and the previous year's last working days unit's price; for measuring the % for 3 years, the last working day unit price and the 3 year priors last working days units price is compared. This parameter calculates short term, mid-term and long-term return.
- *Volatility (Risk Measurement)*: In this performance measures the variability in a mutual funds return is considered. A mutual fund whose return shows more variability, carries higher risk. SAHA used standard deviation to calculate the volatility of a mutual fund. Every mutual fund is evaluated in their own category. In this way, the volatility of the stock-weighted fund preferred by the investor with a high-risk appetite cannot be compared with the volatility of the fixed-income bond-weighted fund preferred by the investor with a low-risk appetite.

$$Standard\ Deviation = \frac{\sqrt{\sum (x_i - \bar{x})}}{n}$$

- *Sharpe Ratio*: When comparing two mutual funds which are in the same category and bring in the same return volatility is a good indicator of risk. However, when comparing mutual funds which are different both in terms of volatility and return, there needs to be a parameter that evaluates risk and return on the same aspect. In that sense, to evaluate risk adjusted return SAHA choses to use Sharpe ratio. The Sharpe ratio evaluates performance as risk-

adjusted by deducting the risk-free rate from gross yield and dividing the resulting net return by volatility.

$$\text{Sharpe Ratio} = (\text{Return} - \text{Risk Free Rate}) / \text{Volatility}$$

- *Benchmark Performance (return measurement);* This performance measurement compares the mutual fund's monthly (yearly, 3 years) return to the belonging fund categories' average monthly (yearly, 3 years) return. This comparison is done based on taking the percentage of the months where the mutual fund is above the average of the fund category. This parameter shows the performance of the mutual fund when compared to its benchmarks.
- *Timing Skills Measurement:* one of the mutual fund's performance measure is the ability of the fund's manager reaction to the changes in the market condition. These reactions can include offensive or defensive reactions depending on the mutual fund's bylaws and can include actions such as increase/decrease/addition/subtraction of assets in the mutual funds. The results of these actions make up the timing skills of the fund manager. SAHA evaluates timing ability by measuring the extent to which the fund's return diverges from the return of its category. Ideally, In the period when the return of the category the fund is included in is positive, the return of the fund should be higher, and in the period when the return of the category that the fund is included in is negative, the return of the fund should be either positive or a low negative.

After the performance measures are evaluated, every mutual fund is rated in their own category. The five performance measures make up the overall score for the rankings. After the overall scores are calculated top 10% in their own category are given 5 stars, the following 22,5% are given 4 stars, the next 35% are

given 3 stars, following 22,5% is given 2 stars and the last 10% is given 1 star.

2.7.2.2 *Ludens advanced financial services and consulting ltd. sti. (LUDENS):*

LUDENS Advanced Financial Services and Consulting Ltd. Sti. which is one of the two firms whom specializes in rating funds in Turkey's financial ecosystem was founded in September 2014. Their main mission was to establish beneficial tools for both investors and market professionals and to support decisions concerning investments by altering mathematical methods into daily applications (***LUDENS Advanced Financial Services and Consulting Ltd. Sti., 2022***). In their fund rating system, they use a rating and ranking service which takes into account the mutual funds' performance and the performance of private pension mutual funds which are managed by the collective investment institutions in the country. In their fund rating system, the mutual funds are rated by use of an authentic, mathematical and quantitative method which is developed by the LUDENS company.

The fund rating system is based on two main criteria:

- Risk adjusted performance (alpha)
- Stability of performance

In this method, funds are grouped first. This grouping is mainly based on the investment strategies of the funds and the distribution of benchmark portfolios disclosed by the fund. Thus, for example, for private pension mutual funds, fund types such as balanced, stock, public debt fund and etc. categories are formed. After the creation of these categories, analyzes are made regarding the two criteria described below.

Risk adjusted performance (alpha): The main focus of this method is to identify the specific performance that results from the skill of the fund manager. The aim here is to purify the effect of the dominant position in the financial markets on the total fund performance. For this purpose, it is based on the return-based style analysis developed by Sharpe. This analysis can simply be expressed as finding the weighted average of the set of market

indices with returns closest to the fund being analyzed. Based on the style analysis, the performance of the portfolio can be expressed as follows:

$$R_{Pt} + R_{ft} = \alpha_p + \sum_{k=1}^K \beta_{Pk}(F_{kt} - R_{ft}) + \varphi_{Pt}$$

Where, R_{Pt} is the return of the fund, F_{kt} is the return of the k index, R_{ft} is the risk-free return, β_{Pk} is the fund's sensitivity to the k index and φ_{Pt} is the error term.

Here, alpha is a measure of performance resulting from the management skill of an actively managed fund.

The returns used in the application are weekly and the analysis period is 3 years. As can be understood from the above expression, the returns used are free of risk-free returns. In addition, since the basis of the methodology is to determine the performance of the portfolio manager, an arrangement has been made accordingly in the calculation of the returns, and the expenses that the manager cannot control (the pension company's share of the fund operating expenses, notary public, etc.) are not included in the calculation.

Stability of performance: Although a fund's positive alpha for a given period is a significant criterion on its own, the stability of this situation is thought to be a distinctive feature for the investor. From this point of view, the secondary focus of the method is the stability of the performance. The performance that is meant here and whose stability is sought is the performance originating from the management skills of the fund manager in the light of the explanations in the first part. The criterion used for this purpose is the retrospective positive alpha number. While calculating this criterion, the alpha series of the fund for the past 156 weeks (3 years) is used. If more than 50% of the 156 alphas are positive, this fund is a stable fund.

While determining the number of stars in the rating, first of all, the funds were divided into two groups as their alpha values, positive and negative. Funds with negative alpha are given 1 star. Funds with positive alpha are ranked according to their alpha size. This fund group, which is ordered from largest to smallest according to alpha, is then divided into four

equal parts and 5, 4, 3 and 2 stars are given to these funds, starting from the first part. Then, the stability criterion is considered for the funds that receive 5 stars. Funds that meet this criterion are assigned the phrase "5I". Although it has received 5 stars, there may be funds whose stability criteria cannot be examined due to insufficient data. These funds are awarded only 5 stars and there is a description next to the fund regarding this situation ((LUDENS Advanced Financial Services and Consulting Ltd. Sti., 2022).

Chapter 3: Methodology

3.1 Performance Criteria

In this section, we will outline the performance criteria used to measure the fund's performance. Our evaluation and ranking methodology will encompass various performance measurement techniques that can be divided into eight main pillars:

Return Performance Measures: These measures assess the fund's performance based on its returns over a given period of time, including metrics such as total return, average annual return, and compound annual growth rate.

General Risk Benchmark Comparison Performance Measures: These measures evaluate the fund's performance relative to a benchmark or set of benchmarks, taking into account various risk factors such as market volatility, interest rate changes, and currency fluctuations.

Dynamic Performance Measures in Extreme Market Conditions: These measures analyze the fund's performance during periods of extreme market conditions, such as market crashes, recessions, or rapid changes in interest rates, to assess its ability to weather economic turbulence.

Relative Performance Measures According to Different Market Conditions: These measures compare the fund's performance to that of its peers or competitors, taking into account the specific market conditions in which it operates.

Out of Group Performance Measures: These measures assess the fund's performance relative to similar funds outside its peer group, providing a broader perspective on its relative strengths and weaknesses.

Absolute Risk Level Performance Criteria: These measures evaluate the fund's performance based on its risk level, including metrics such as standard deviation, value at risk, and maximum drawdown.

Risk-Adjusted Performance Measures: These measures evaluate the fund's performance based on its risk-adjusted returns, including metrics such as the Sharpe ratio, Treynor ratio, and Jensen's alpha.

Management Performance Measures: These measures evaluate the fund's performance based on the effectiveness of its management team, including metrics such as fund flows, turnover rate, and management fees.

By incorporating these eight pillars of performance measurement techniques, our methodology aims to provide a comprehensive and multi-dimensional evaluation of the fund's performance.

3.1.1 Return Performance Measures

3.1.1.1 Annual return. Annual Return is the return generated from the mutual in a one-year period. The calculation method is as follows.

$$\text{Annual Return} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where, P_t is the last price of the mutual fund and P_{t-1} equals to the price one year prior to the last price.

3.1.1.2 Annualized average excess return. To annualize the benchmark and portfolio assets, observations should be scaled on an annual basis by increasing the annual compound returns and taking the root according to the total number of observations.

$$R_{ap} = \left(\prod_{i=1}^n (1 + R_p) \right)^{\frac{1}{n}} - 1$$

$$R_{ab} = \left(\prod_{i=1}^n (1 + R_b) \right)^{\frac{1}{n}} - 1$$

Where, R_p is the portfolio return, R_b equals to benchmark returns and n is the total number of observations.

3.1.1.3 Annualized average geometric excess return. This performance measure gives the annualized average geometric excess return for the mutual fund. The calculation method is as follows.

$$\text{Annualized Average Geometric Excess Return} = \frac{1 + R_{pa}}{1 + R_{ba}} - 1$$

Where R_{pa} is the annualized portfolio return and R_{ba} is the annualized benchmark return.

3.1.1.4 Annualized average geometric return. This performance measure gives the annualized average geometric return for the mutual fund. The calculation method is as follows.

$$\text{Annualized Average Geometric Return} = \sqrt[n]{\text{prod}(1 + R_a)^{\text{scale}}} - 1$$

Where, R_a is the asset return and $scale$ is the total observations in a year and n is the total number of observations.

3.1.1.5 Geometric average return. The Geometric Average Return is used to calculate the average rate per period of investments compounded over multiple periods.

$$\text{Geometric Average Return} = \sqrt[n]{\prod (1 + R_a)} - 1$$

Where, R_a is the asset return.

3.1.1.6 Total return. Total return, in terms of yield performance, is the actual return of an investment or an investment pool over a certain evaluation period. It includes the interest, capital gain, dividends, and distributions that occurred over a specific time frame.

$$\text{Total Return} = \prod_{i=1}^n (R_a[i] + 1)$$

Where, R_a is the asset return, n is the total number of observations.

This calculation also done for benchmarks and risk-free rates.

3.1.1.7 D ratio. D ratio is similar to Bernado Ledoit Ratio, but it takes into account the frequency of positive and negative returns. It can be used to compare portfolio performances. D Ratio values range from 0 to infinity. The lower the D Ratio, the better the portfolio performance. A value of 0 indicates no returns less than 0, and infinity indicates no returns greater than 0.

The calculation method is as follows;

$$\text{D Ratio} = \frac{n_d \times \sum_{i=1}^n \max(-R_i, 0)}{n_u \times \sum_{i=1}^n \max(R_i, 0)}$$

Where R_i is the return of i^{th} asset, R_i is the number of total observations, n_d is the number of observations which are lower than 0 and n_u is the number of observations which are bigger than 0.

3.1.1.8 Excess return. Excess return is defined as the return on assets that exceeds the "risk-free interest rate" for the relevant period. The calculation method is as follows;

$$Excess\ Return = R_a - R_f$$

Where, R_a is the asset return and R_f is the risk free interest rate.

3.1.1.9 Lower confidence level mean. The Lower Confidence Level Mean calculates attributes based on the mean of the series of observations at a low confidence level. The calculation method is as follows;

$$Lower\ Confidence\ Level\ Mean = \bar{R}_a + \sqrt{\frac{var(R_a)}{n}} \times t_a$$

Where, R_a is the asset return, n is the number of total observations and t_a is the confidence interval of the t distribution table.

3.1.1.10 Mean absolute deviation. To calculate the Mean Absolute Deviation, the absolute value of the differences between the return and the average return is taken and divided by the total return (observations). The calculation method is as follows;

$$Mean\ Absolute\ Deviation = \frac{\sum_{i=1}^n |R_i - \bar{R}|}{n}$$

Where R_i is the i^{th} asset return, $\bar{R}$ is the average return and n is the number of total observations.

3.1.1.11 Prospect ratio. Prospect Ratio is a ratio used to penalize losses as most traders feel more losses than gains. The calculation method is as follows;

$$Prospect\ Ratio = \frac{\sum_{i=1}^n (\max(R_i, 0) + 2,25 \times \min(R_i, 0) - MAR)}{n \times \sigma_D}$$

Where R_i is the i^{th} asset return, n is the number of total observations, MAR is the acceptable minimum return and σ_D is the downside risk.

3.1.1.12 Quarterly return. Quarterly return is the return calculated by taking into consideration a 3 period time span. The calculation method is as follows;

$$R_{quarterly} = \left(\frac{P_t}{P_{t-1}}\right)^{\frac{1}{t}} - 1$$

Where, t is the period (year*4), P_t is the price at the end of t quarter period and P_{t-1} is the price at the end of previous t quarter period.

3.1.1.13 Relative return. Relative Return calculates the ratio of cumulative performance over time for two assets. The calculation method is as follows;

$$Relative\ Return = \frac{cumprod(1 + R_a)}{cumprod(1 + R_b)}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.1.14 Semiannual return. Semiannual return is the return calculated by taking into consideration a 6-month time span. The calculation method is as follows:

$$R_{semiannual} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where, t is the period (year*2), P_t is the price at the end of 6-month period and P_{t-1} is the price at the end of previous 6-month period.

3.1.1.15 Upper confidence level mean. The Upper Confidence Level Mean calculates attributes based on the mean of the series of observations at a high confidence level. The calculation method is as follows;

$$Upper\ Confidence\ Level\ Mean = \bar{R}_a - \sqrt{\frac{var(R_a)}{n}} \times t_\alpha$$

Where, R_a is the asset return and t_α shows the confidence level of t distribution table.

3.1.2 General Risk Benchmark Comparison Performance Measures

3.1.2.1 Active premium. Active Premium ratio is calculated by subtracting the annualized benchmark return from the annualized return on investment. The calculation method is as follows:

$$\text{Active Premium} = R_a - R_b$$

Where, R_a is the annualized asset return and R_b is the annualized benchmark return.

3.1.2.2 Beta cokurtosis. Beta Cokurtosis measures how an asset in the portfolio has historically responded to extreme benchmark returns. In case the benchmark has excessively positive or negative returns, the asset with negative Beta CoKurtosis provides portfolio protection. The calculation method is as follows:

$$\text{Beta CoKurtosis} = \frac{\sum_{i=1}^n (R_a - \bar{R}_a) x (R_b - \bar{R}_b)^3}{\sum_{i=1}^n (R_b - \bar{R}_b)^4}$$

Where, R_a is the asset return, R_b is the benchmark return and n is the total number of observations.

3.1.2.3 Beta coskewness. Beta Cokurtosis measures how an asset in the portfolio has historically responded to extreme benchmark returns. In case the benchmark has excessively positive or negative returns, the asset with positive Beta CoSkewness provides portfolio protection. The calculation method is as follows:

$$\text{Beta CoSkewness} = \frac{\sum_{i=1}^n (R_a - \bar{R}_a) x (R_b - \bar{R}_b)^2}{\sum_{i=1}^n (R_b - \bar{R}_b)^3}$$

Where, R_a is the asset return, R_b is the benchmark return and n is the total number of observations.

3.1.2.4 Beta covariance. Beta CoVariance helps investors determine how much risk they are willing to take for return, it is used as a risk-reward metric. The calculation method is as follows:

$$Beta\ CoVariance = \frac{\sum_{i=1}^n (R_a - \overline{R_a})x(R_b - \overline{R_b})}{\sum_{i=1}^n (R_b - \overline{R_b})^2}$$

Where, R_a is the asset return, R_b is the benchmark return and n is the total number of observations.

3.1.2.5 Capm beta. CAPM Beta is the beta model for the variance and covariance of an asset's initial portfolio. It is used to determine the diversification potential. The calculation method is as follows;

$$CAPM\ Beta = \frac{COV(R_a, R_b)}{\sigma_b^2}$$

Where, R_a is the asset return, R_b is the benchmark return σ_b is the benchmark volatility.

3.1.2.6 Capm cml. The Capital Market Line (CAPM CML) relates the expected return on an efficient market portfolio to risk. CML describes the reward/risk line that a leveraged portfolio will cover. Therefore, a portfolio made of the same assets according to CAPM cannot be on the Capital Market Line (CML). The calculation method is as follows;

$$CAPM\ CML = \overline{R_f} + SharpeRatio \times \overline{R_a}$$

Where, R_a is the asset return and R_f is the risk free interest rate.

3.1.2.7 Covariance. CoVariance is a measure of the directional relationship between the returns of two risky assets. Positive CoVariance indicates that the asset returns move together, while negative CoVariance means they move in opposite directions.

$$Covariance = \frac{\sum_{i=1}^n (R_a - \bar{R}_a) \times (R_b - \bar{R}_b)}{n}$$

Where, R_a is the asset return, R_b is the benchmark return and n is the total number of observations.

3.1.2.8 Ewma correlation. EWMA Correlation estimates for time t of any time interval. One of the advantages of the EWMA approach is the greater emphasis on the final data. Another advantage is the EWMA forecasts show instant changes. The calculation method is as follows:

$$EWMA\ Correlation = \frac{\sigma_{ewma}^2}{\sigma_a \times \sigma_b}$$

Where σ_{ewma} is the EWMA volatility, σ_a is the asset volatility and σ_b is the benchmark volatility.

3.1.2.9 Henriksson-merton market timing – alpha. The basic idea of the Henriksson-Merton Market Timing test is to perform a multiple regression with the dependent variable (the exit portfolio return and the second variable that mimics the return as an option). The second variable is 0 when the market excess yield is zero or below zero, and 1 when it is above it. In this calculation the alpha value is calculated. The calculation method is as follows:

$$R_p - R_f = \alpha + \beta(R_b - R_f) + \gamma D + \epsilon_p$$

Where, $D = \max(0, R_b - R_f)$ is the top market return, γ is the market timing ability, R_p is the return on portfolio, R_f is the risk-free return and R_b is the benchmark return.

3.1.2.10 Henriksson-merton market timing – beta. The basic idea of the Henriksson-Merton Market Timing test is to perform a multiple regression with the dependent variable (the exit portfolio return and the second variable that mimics the return as an option). The second variable is 0 when the market excess yield is zero or below zero, and 1 when it is above it. In this calculation the beta value is calculated. The calculation method is as follows;

$$R_p - R_f = \alpha + \beta(R_b - R_f) + \gamma D + \epsilon_p$$

Where, $D = \max(0, R_b - R_f)$ is the top market return, γ is the market timing ability, R_p is the return on portfolio, R_f is the risk free return and R_b is the benchmark return.

3.1.2.11 Henriksson-merton market timing – gamma. The basic idea of the Henriksson-Merton Market Timing test is to perform a multiple regression with the dependent variable (the exit portfolio return and the second variable that mimics the return as an option). The second variable is 0 when the market excess yield is zero or below zero, and 1 when it is above it. In this calculation the gamma value is calculated. The calculation method is as follows;

$$R_p - R_f = \alpha + \beta(R_b - R_f) + \gamma D + \epsilon_p$$

Where, $D = \max(0, R_b - R_f)$ is the top market return, γ is the market timing ability, R_p is the return on portfolio, R_f is the risk free return and R_b is the benchmark return.

3.1.2.12 Kendall correlation. Kendall Correlation is a non-parametric test that measures the strength of linear correlation between two variables. The calculation method is as follows;

$$Kendall\ Correlation = \frac{2(N_c + N_d)}{n(n - 1)}$$

Where, N_c is the concordant number and N_d is the discordant number.

3.1.2.13 Pearson correlation. The Pearson Correlation coefficient is a test statistic that measures the linear relationship between two continuous variables. Since it is based on the covariance method, it is one of the best methods to measure the relationship between related variables. It gives information about the direction of the relationship as well as the magnitude of the relationship or correlation. The calculation method is as follows;

$$Pearson\ Correlation = \frac{COV(R_a, R_b)}{\sigma_a \times \sigma_b}$$

Where, R_a is the asset return, R_b is the benchmark return, σ_a is the asset volatility and σ_b is the benchmark volatility.

3.1.2.14 Spearman correlation. Spearman Correlation is a non-parametric test used to measure the degree of linear relationship between two variables.

$$Spearman\ Correlation = 1 - \frac{6 \sum_{i=1}^n (R_a[i] - R_b[i])^2}{n(n^2 - 1)}$$

Where, R_a is the asset return, R_b is the benchmark return and n is the number of observations.

3.1.2.15 Tracking error. Tracking Error is a measure of the unexplained part of benchmark-related performance.

$$Tracking\ Error = \sqrt{\sum \frac{(R_a - R_b)^2}{len(R_a)}}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.3 Dynamic Performance Measures in Extreme Market Conditions

3.1.3.1 Drawdown. Drawdown, in the context of finance and investments, is a measurement that represents the decline from a peak to a trough for a specific investment or fund. It's a way of expressing the worst period of loss for an investment, which investors often use to understand potential risks and the resilience of an investment strategy.

$$\text{Drawdown} = \text{Peak Value} - \text{Through Value}$$

3.1.4 Relative Performance Measures According to Different Market Conditions

3.1.4.1 Downside capture. Downside Capture measures the percentage of market loss an operator incurs when equity markets are negative.

$$\text{Downside Capture} = \sum \frac{(R_a, R_b < 0)}{(R_b, R_b < 0)}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.4.2 Downside frequency. Downside Frequency is calculated by dividing the number of returns below the minimum acceptable return (MAR) by the total return (observation).

$$\text{Downside Frequency} = \sum_{i=1}^n \frac{\min[(R_i - \text{MAR}), 0]}{R_i \times n}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable return and n is the total number of observations.

3.1.4.3 Downside percentage. Downside Percentage is a measure of the number of periods the investment has outperformed the benchmark when the benchmark is negative.

$$\text{Downside Percentage} = \frac{\|(R_a, R_a > R_b, R_b < 0)\|}{\|(R_b, R_b < 0)\|}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.4.4 Downside number. The Downside Count is a measure of the periods in which the investment has fallen while the benchmark is down.

Downside Number doesn't have a standardized one since it's a descriptive statistic rather than a mathematical calculation. It's the count of periods (days, months, quarters, etc.) when both the investment return and the benchmark return are less than zero.

3.1.4.5 Downside potential. Downside Potential is the average of negative returns that exceed the minimum acceptable return (MAR) value.

$$\text{Downside Potential} = \sum_{i=1}^n \frac{\min[(R_i - MAR), 0]}{n}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable return and n is the total number of observations.

3.1.4.6 Gain percentage. Gain Percentage compares the days when the return on assets is positive with the days when the benchmark return is positive during the relevant period.

$$\text{Gain Percentage} = \frac{\|R_a > 0\|}{\|R_b > 0\|}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.4.7 Up down ratio. Up Down Ratio offers an insight into the behavior of an investment relative to a certain benchmark. It's a comparative figure that allows the investor to understand how often the investment performs positively against the benchmark (Upside Frequency) versus how often it underperforms (Downside Frequency).

$$Up\ Down\ Ratio = \frac{Upside\ Frequency}{Downside\ Frequency}$$

3.1.4.8 Upside capture. Upside Capture is equal to the percentage of market earnings generated during the stock market boom period.

$$Upside\ Capture = \frac{\sum(R_a, R_b > 0)}{\sum(R_b, R_b > 0)}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.4.9 Upside frequency. Upside Frequency is calculated by dividing the number of returns above the minimum acceptable return (MAR) by the total return (observations).

$$Upside\ Frequency = \sum_{i=1}^n \frac{\max[(R_i - MAR), 0]}{R_i \times n}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable return and n is the total number of observations.

3.1.4.10 Upside percentage. Upside Percentage is a measure of the number of times an investment outperformed the benchmark when the benchmark was positive.

$$Upside\ Percentage = \frac{\|(R_a, R_a > R_b, R_b > 0)\|}{\|(R_b, R_b > 0)\|}$$

Where, R_a is the asset return and R_b is the benchmark return.

3.1.4.11 Upside potential. Upside Potential only considers Downside Deviation with returns higher than the specified threshold.

$$Upside\ Potential = \sum_{i=1}^n \frac{R_i - MAR}{\delta_{MAR}}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable return, n is the total number of observations and δ_{MAR} represents Downside Deviation.

3.1.4.12 Upside potential ratio. Upside Potential Ratio is the rate of which performance is linked to downside risk.

$$Upside\ Potential = \frac{\sum_{i=1}^n (R_i - MAR)}{\delta_{MAR}}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable return, n is the total number of observations and δ_{MAR} represents Downside Deviation.

3.1.5 Out of Group Performance Measures

3.1.5.1 Hurst index. The Hurst Exponent can be used to measure whether returns are oscillating around the mean, random, or have memory. This approach is often referred to as rescaled range analysis, because Hurst obtains a dimensionless statistic by dividing the range of observations by their standard deviation.

$$Hurst\ Index = \frac{\log|\max(R_i) - \min(R_i)|}{\log(n)}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6 Absolute Risk Level Performance Criteria

3.1.6.1 Annualized downside volatility. Annualized Downside Volatility is the annualized standard deviation of negative returns. This is based on the principle of capturing the volatility of only downward movements. In the distribution of non-systematic return changes, values in both upwards and downwards directions are significantly impacted. This method is used to determine whether the market is in a downward trend or an upward trend.

$$\text{Annualized Downside Volatility} = \sqrt{\sum_{i=1}^n \min(Ra_i - MAR, 0)^2}$$

Where, Ra_i is the i^{th} asset return, n is the total number of observations and MAR is the minimum acceptable return.

3.1.6.2 Annualized ewma volatility. Annualized EWMA Volatility is the annualized version of the daily Exponentially Weighted Moving Average (EWMA) volatility model.

$$\text{Annualized EWMA Volatility} = \sigma_{\text{daily}} * \sqrt{\text{scale}}$$

Where, σ_{daily} is the EWMA volatility and scale is the total number of observations.

3.1.6.3 Annualized upside volatility. Annualized Upside Volatility is the annualized standard deviation of positive returns. It is based on the principle of capturing the volatility of only upward movements

$$\text{Annualized Downside Volatility} = \sqrt{\sum_{i=1}^n \max(Ra_i - MAR, 0)^2}$$

Where, Ra_i is the i^{th} asset return, n is the total number of observations and MAR is the minimum acceptable return.

3.1.6.4 Downside volatility. Downside Volatility, similar to SemiDeviation, excludes positive returns when calculating risk. Instead of using average return or zero, it employs the Minimum Acceptable Return (MAR) as suggested by Sharpe (which can be the historical average return or zero). It measures the variation in poor performance below the minimum target rate.

$$\text{Downside Volatility} = \sqrt{\frac{\sum_{i=1}^n \min(Ra_i - MAR, 0)^2}{n}}$$

Where, Ra_i is the i^{th} asset return, n is the total number of observations under MAR value and MAR is the minimum acceptable return.

3.1.6.5 Excess kurtosis. Excess Kurtosis is the kurtosis calculated using the moment method, after subtracting the value of 3. Generally, a rational investor should prefer an asset with a lower negative excess kurtosis value for more predictable returns.

$$\text{Excess Kurtosis} = \frac{\sum_{i=1}^n (R_i - \bar{R})^4 \times n}{(n-3) \times ((\text{var}(R) - (n-1)))^2}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6.6 Fisher kurtosis. The Fisher Kurtosis method corresponds to the usual unbiased sample variance definition, even though complete unbiasedness for kurtosis is not possible.

$$\text{Fisher Kurtosis} = \frac{(n+1) \times (n-1)}{(n-1) \times (n-3)} \frac{\frac{\sum_{i=1}^n (R_i)^4}{n}}{(\sum_{i=1}^n \frac{(R_i)^2}{n})^2} - \frac{3(n-1)}{n+1}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6.7 Fisher skewness. The Fisher Skewness method corresponds to the usual unbiased sample variance definition, even though complete unbiasedness for skewness is not possible.

$$Fisher\ Skewness = \frac{\sqrt{n \times (n-1) \times \sum_{i=1}^n \frac{R_i^3}{n}}}{\sqrt{n-2} \times \sum_{i=1}^n \left(\frac{R_i^3}{n}\right)^{3/2}}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6.8 Gain deviation. Gain Deviation is the standard deviation of positive returns.

$$Gain\ Deviation = \sqrt{\frac{\sum_{i=1}^n \max(0, R_i)^2}{n}}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6.9 Kurtosis. Kurtosis is a statistical measure used to describe the distribution of observed data around the mean. It measures the "tailedness" of the distribution, which can be an important factor in assessing the risk level of an investment. High kurtosis indicates a higher probability of extreme outcomes, which can be viewed as increased risk.

$$Kurtosis = \frac{\sum_{i=1}^n \frac{(R_i - \bar{R})^4}{n}}{\sigma_a^4} - 3$$

Where, R_i is the i^{th} asset return, σ_a is the standard deviation of the data and n is the total number of observations.

3.1.6.10 Loss deviation. Loss Deviation is the standard deviation of negative returns. It is related to Downside Deviation, which subtracts the benchmark from the investment to determine periods of loss.

$$Loss\ Deviation = \sqrt{\frac{\sum_{i=1}^n \min(0, R_i)^2}{n}}$$

Where, R_i is the i^{th} asset return and n is the total number of observations.

3.1.6.11 Lower partial moment. The Lower Partial Moment has various features that make it a more appropriate risk measure compared to variance, as it captures the negative deviation from the reference point. The reference point could be the mean or a certain threshold that is meaningful to the investor. We have taken it as the mean in our study.

$$Lower\ Partial\ Moment = \frac{\sum_{i=1}^n \max(MAR - R_i, 0)^l}{n}$$

Where, R_i is the i^{th} asset return, n is the total number of observations, MAR is the minimum acceptable return and l is the moment of return.

3.1.6.12 Semi deviation. Semi Deviation is an alternative downside risk measure that can be used instead of standard deviation. In the Semi Deviation calculation, the average return is used in place of the MAR term in the Downside Deviation formulation, and the total number of observations is used for the length.

$$Semi\ Deviation = \sqrt{\frac{\sum_{i=1}^n \min(R_i - \bar{R}, 0)^2}{n}}$$

Where, R_i is the i^{th} asset return, $\bar{R}$ is the mean of all returns and n is the total number of observations.

3.1.6.13 Skewness. Skewness is a measure used to determine the degree of deviation from a normal distribution. It expresses the asymmetry in the statistical distribution.

$$Skewness(sample) = \frac{\frac{\sum_{i=1}^n (\frac{R_i - \bar{R}}{\sigma_{sp}})^3}{n}}{(n-1) \times (n-2)}$$

Where, R_i is the i^{th} asset return, $\bar{R}$ is the mean of all returns, n is the total number of observations and σ_{sp} is the sample standard deviation.

3.1.6.14 Skewness kurtosis ratio. Skewness Kurtosis Ratio is the deviation of Skewness to Kurtosis.

$$Skewness\ Kurtosis\ Ratio = \frac{Skewness}{Kurtosis}$$

3.1.6.15 Standard deviation. Standard Deviation is a statistic that measures the dispersion of observations and is calculated by taking the square root of variance. The more observations deviate from the mean, the greater the deviation. Thus, the more spread out the observations are, the higher the value of Standard Deviation. This calculation is done for all asset returns, benchmarks, risk free rates and also for ewma.

$$Skewness(sample) = \sqrt{\frac{\sum_{i=1}^n R_i - \bar{R}}{n}}$$

Where, R_i is the i^{th} asset return, $\bar{R}$ is the mean of all returns and n is the total number of observations.

3.1.6.16 Systematic risk. Systematic Risk, as defined by Bacon, is a product of beta relative to market risk. Market risk is the standard deviation of the benchmark. Systematic risk, on the other hand, is annualized. It is impossible to control the systematic risk arising from the integrated change in the market through portfolio diversification (Bacon, 2011).

$$\text{Systematic Risk} = \beta \times \sigma_m$$

Where, β is the regression beta and σ_m is market risk.

3.1.6.17 Upside volatility. Upside Volatility is similar to Semi Deviation, but instead of taking average return or zero, it takes returns that remain over the Minimum Acceptable Return (MAR).

$$\text{Upside Volatility} = \sqrt{\frac{\sum_{i=1}^n \max(R_i - \text{MAR}, 0)^2}{n}}$$

Where, R_i is the i th asset return, MAR is the minimum acceptable returns and n is the total number of observations.

3.1.6.18 Variance. Variance is a measure of the dispersion among observations, it measures how far each observation is from the average.

$$\text{Variance} = \frac{\sum_{i=1}^n (R_i - \bar{R})^2}{n}$$

Where, R_i is the i^{th} asset return, $\bar{R}$ is the mean of all returns and n is the total number of observations.

3.1.7 Risk-Adjusted Performance Measures

3.1.7.1 Downside deviation. This is a metric that focuses on the variability of returns that fall below a defined minimum acceptable return or a specific target, often zero or the mean return. It calculates the investment's tendency for negative, or 'downside', volatility, helping investors understand potential losses.

Downside Deviation is calculated by taking the standard deviation of the negative values.

3.1.7.2 Kappa. Kappa is a generalized downside adjusted-risk performance measure.

$$Kappa = \frac{R_a - MAR}{\sqrt[l]{\frac{1}{n} \times \sum_{i=1}^n \max(MAR - R_i, 0)^l}}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable returns, l is the Kappa number and n is the total number of observations.

3.1.7.3 Omega sharpe ratio. The Omega-Sharpe Ratio is essentially the Omega Ratio transformed into ranking statistics, a concept familiar from the Sharpe Ratio.

$$Omega\ Sharpe\ Ratio = \frac{R_a - MAR}{\sum_{i=1}^n \frac{\max(MAR - R_i, 0)}{n}}$$

Where, R_i is the i^{th} asset return, MAR is the minimum acceptable returns and n is the total number of observations.

3.1.7.4 Sharpe ratio. Sharpe Ratio, in its most general form, can be expressed as return per unit of risk. In the classic scenario, the unit of risk is the standard deviation of returns.

$$\text{Sharpe Ratio} = \frac{\overline{R_a - R_f}}{\sigma_{R_a}}$$

Where, R_a is the asset return, R_f is the risk-free return and σ_{R_a} is the standard deviation of assets.

3.1.7.5 Sortino ratio. The Sortino Ratio, by using only downside semivariance as a measure of risk for better calculation of excess performance, has been proposed as an improvement on the Sharpe Ratio.

$$\text{Omega Sharpe Ratio} = \frac{\overline{R_a - MAR}}{\sigma_{MAR}}$$

Where, R_a is the asset return, σ_{MAR} is the downside deviation and MAR is the minimum acceptable return.

3.1.7.6 Upside deviation. This term signifies a measurement of the statistical dispersion of returns exceeding a specified minimum return, often zero or the mean return. It essentially quantifies the fluctuations of an investment's outcomes when they surpass a predetermined level, offering insight into its potential for positive, or 'upside', volatility.

Upside Deviation is calculated by taking the standard deviation of the positive values.

3.1.8 Management Performance Measures

3.1.8.1 Famas measure. The Famas Measure, unlike Jensen's Alpha, calculates the return exceeding the expected based on the Total Risk premium, not the systematic risk premium.

$$Famas\ Measure = (\overline{R_a} - R_f) - \frac{\sigma_a}{\sigma_b} \times (\overline{R_b} - R_f)$$

Where, R_a is the asset return, R_b is the benchmark return and R_f is the risk-free return.

3.1.8.2 Information ratio. Information Ratio is the dividing of Active Premium to Tracking Error.

$$Information\ Ratio = \frac{Active\ Premium}{Tracking\ Error}$$

3.2 The Programming Language

The Python programming language was chosen as the main interpreter for the software program for the fund rating system. This decision was made because the system was intended to be developed into an application that could be easily used and further developed, and Python is a versatile and high-level programming language that can accommodate future changes and updates.

However, the methodology of rating funds required numerous calculations that involved symbolic and complex mathematics. After conducting research, it was discovered that these types of calculations are more commonly done on programming languages such as R, MATLAB, or Julia, as they are more oriented towards solving complex mathematics. While Python has many scientific libraries and packages that are widely used to solve some mathematical equations such as Pandas, NumPy, or Python Math Module, none of them were geared towards solving symbolic or complex mathematical equations.

During the research process, it was observed that some of the simpler formulas could be written by breaking them down into their building blocks. However, the more complex formulas could not be broken down in this way. Writing each formula

in this manner would have resulted in a very complex and messy software program, which would have significantly slowed down the calculations.

After conducting considerable research, it was determined that the sympy module was a suitable solution. sympy is a Python library for symbolic mathematics, which enables users to manipulate mathematical expressions symbolically, solve equations, perform calculus operations, and generate LaTeX code from expressions. This module provides a range of mathematical operations, such as differentiation, integration, equation solving, simplification, and manipulation of mathematical expressions. It also supports complex numbers, polynomial manipulation, and matrix operations.

One of the main advantages of using sympy is its ability to handle symbolic or complex mathematical equations that cannot be easily broken down into simpler building blocks. This makes sympy an ideal choice for mathematical calculations in areas such as physics, engineering, and finance, where complex mathematical expressions are common. It is worth noting that sympy is an uncommon module for Python and has not been updated frequently. However, it remains a valuable tool for advanced mathematical computations, particularly in cases where other Python libraries and packages are inadequate for handling complex mathematical expressions.

In summary, sympy is a Python library that provides a powerful set of tools for solving symbolic and complex mathematical problems, making it a valuable addition to any project that requires advanced mathematical computations, such as the fund rating system.

After confirming that the sympy module was suitable for integrating complex mathematical formulas into the Python software system, the first step of the methodology was to incorporate the formulas into code within the Jupyter Notebook computational document system. This was an important step because the sympy codes could be displayed as symbolic formulas within the Jupyter Notebook IPython application system, which allowed for easier verification and interpretation of the mathematical expressions.

The formulas were first written in the Jupyter Notebook system and checked for correctness by visually inspecting the formulations. This involved comparing the

code to the original mathematical formulas to ensure that the correct expressions were being implemented. Once the formulations were visually verified, numerical values were assigned to the variables in the code to verify the resulting outputs. This involved running the code with different numerical inputs and comparing the output to known values or expected results.

To ensure the accuracy and reliability of the implementation, this verification process was repeated several times for each formula, with different numerical values assigned to the variables each time. This allowed for a more comprehensive check of the code's correctness and minimized the risk of errors being introduced due to incorrect implementation or syntax.

Examples of the symbolic formulas displayed within the Jupyter Notebook system and their solutions with some dummy values are given in the figures below. These figures illustrate how the sympy codes are displayed as mathematical expressions, which can be more easily interpreted by researchers and readers of the thesis.



The screenshot shows a Jupyter Notebook cell with the following code:

```
In [3]: Rap=sp.IndexedBase('Rap')
Rab=sp.IndexedBase('Rab')
scale,n,a=sp.symbols('scale n a')
i=sp.symbols('i',cls=Idx)
values=[1,2,3,4,5]
lenval=len(values)-1
AnnualizedAverageGeometricReturn=(sp.Product((1+Rap[i]),(1,1,n))**(scale))**(1/n)-1
AnnualizedAverageGeometricReturn
```

The output shows the symbolic formula:

$$\left(\left(\prod_{Idx(i)=1}^n (Rap_{Idx(i)} + 1) \right)^{scale} \right)^{\frac{1}{n}} - 1$$

Figure 1. Jupyter Notebook Annualized Average Geometric Return Formula Creation



The screenshot shows a Jupyter Notebook cell with the following code:

```
In [11]: Rap=sp.IndexedBase('Rap')
Rab=sp.IndexedBase('Rab')
scale,n,d=sp.symbols('scale n a d')
i=sp.symbols('i',cls=Idx)
values=[1,2,3,4,5]
lenval=len(values)-1
AnnualizedAverageGeometricReturn=(sp.Product((1+Rap[i]),(1,1,n))**(scale))**(1/n)-1
Print(AnnualizedAverageGeometricReturn.subs(n,1).subs(d,lenval).doit()).subs({Rap[i]: values[i] for i in range(len(val
```

The output shows the numerical result:

```
Out[11]: 1567.1157828894306
```

Figure 2. Jupyter Notebook Annualized Average Geometric Return with Values

```
In [18]: MAR=smp.symbols('MAR')
Ra=IndexedBase('Ra')
delta_d=IndexedBase('delta_d')
i=smp.symbols('i', integer=True)
values=[1,2,3,4,5]
ProspectRatio=smp.Sum(smp.Max(Ra[i],0)*(2.25*(smp.Min(Ra[i],0))-MAR, -(i,0,n))/(n*delta_d))
ProspectRatio

Out[18]: 
$$\sum_{i=0}^n \frac{(-MAR + \max(0, Ra_i) + 2.25 \min(0, Ra_i))}{n\delta_d}$$

```

Figure 3. Jupyter Notebook Propect Ratio Formula Creation

```
In [20]: MAR=smp.symbols('MAR')
Ra=IndexedBase('Ra')
delta_d=IndexedBase('delta_d')
i=smp.symbols('i', integer=True)
values=[1,2,3,4,5]
ProspectRatio=smp.Sum(smp.Max(Ra[i],0)*(2.25*(smp.Min(Ra[i],0))-MAR, -(i,0,n-1))/(n*delta_d))
ProspectRatio.subs(n,len(values)).subs(delta_d,0.5).doit().subs([(Ra[i], values[i]) for i in range(len(values))]).subs(
Out[20]: 5.9
```

Figure 4. Jupyter Notebook Prospect Ratio with Values

```
In [24]: UpsideFrequency=smp.Sum(smp.Min((Ra[i]-MAR),0)/(Ra[i]*n),(i,1,n))
UpsideFrequency

Out[24]: 
$$\sum_{i=1}^n \frac{\min(0, -MAR + Rb_i)}{nRb_i}$$

```

Figure 5. Jupyter Notebook Upside Frequency Formula Creation

```
In [37]: UpsideFrequency=smp.Sum(smp.Min((Ra[i]-MAR),0)/(Ra[i]*n),(i,0,n-1))
values=[2,3,4,5,6]
float(UpsideFrequency.subs(n,len(values)).subs([(Ra[i], values[i]) for i in range(len(values))]).doit().subs(MAR,5))

Out[37]: -1.2833333333333334
```

Figure 6. Jupyter Notebook Upside Frequency with Values

```
Ra=IndexedBase('Ra')
Rb=IndexedBase('Rb')
i=smp.symbols('i', Integer=True)
n=smp.symbols('n')
values=[1,2,3,4,5]
FisherKurtosis=((n+1)*(n-1))/((n-2)*(n-3))*((smp.Sum(Ra[i]**4/n,(i,0,n-1))/(smp.Sum(Ra[i]**2/n,(i,0,n-1))**2)-(3*(n-1)
FisherKurtosis


$$\frac{(n-1)(n+1)}{(n-3)(n-2)} \left( \frac{\sum_{i=0}^{n-1} \frac{R_i^4}{n^2}}{\left( \sum_{i=0}^{n-1} \frac{R_i^2}{n} \right)^2} - \frac{3n-3}{n+1} \right)$$

```

Figure 7. Jupyter Notebook Fisher Kurtosis Formula Creation

```

Ra=IndexedBase('Ra')
Rb=IndexedBase('Rb')
i=smp.symbols('i', Integer=True)
n=smp.symbols('n')
values=[1,2,3,4,5]
FisherKurtosis=((n-1)*(n-1))/((n-2)*(n-3))*((smp.Sum(Ra[i]**4/n,{i,0,n-1}))/((smp.Sum(Ra[i]**2/n,{i,0,n-1})**2)-(3*(n-1)
float(FisherKurtosis.subs(n,len(values)).doit().subs({Ra[i], values[i]} for i in range(len(values)))).subs({Rb[i], va
-1.5272727272727273

```

Figure 8. Jupyter Notebook Fisher Kurtosis with Values

3.3 Application Construction and Formula Creation in Python

In this section, we describe the methodology for constructing the application and creating formulas to analyze mutual funds using Python. Our approach consists of several components, including data retrieval module, configuration manager, logger, and mathematical models for formula creation. We collaborated with Risk Active company to access mutual fund data from the Turkish market, which is challenging to obtain.

3.3.1 Data retrieval module. The data retrieval module is implemented using the RaDataResponse, RbDataResponse and RfData classes. This classes facilitates extracting mutual fund and Risk Free data from external sources, specifically from Risk Active's online database system. The classes provide methods such as addGroup, addSelect, and get to query the database and retrieve data based on specified criteria. The extracted data is then processed and stored in a structured format for further analysis. In the data retrieval phase the following classes are created to migrate the data from the Risk Active's online system:

TefasResponse: This class inherits from Orm and represents the response from the Tefas API. It has several attributes, such as BORSABULTENFIYAT, FIYAT, FONKODU, and FONUNVAN, among others. The class also includes a method getFundNames() to retrieve the distinct fund names.

TefasRequest: This class is responsible for constructing and managing the request to the Tefas API. It contains attributes like fontip, sfontur, fonkod, and others, as well as methods to set their values, such as setFonTip(),

setSemsıyeFonTip(), and setFonKod(). The getBody() method returns a dictionary containing the request's attributes.

RiskActiveResponse: This class inherits from Orm and represents the response from the Risk Active API. It includes attributes like EN_DUSUK, EN_YUKSEK, ACILIS, and KAPANIS, among others. The class also provides methods to set the values of these attributes, such as setTarih(), setEnDusuk(), setEnYukse(), setAcilis(), and setKapanis().

RequestMethod: This is an enumeration class that defines the possible HTTP request methods: POST, GET, PUT, and DELETE.

BlueRequest: This class manages the construction and execution of HTTP requests, including setting the URL, body, headers, and cookies. The class initializes a request with default values for the body, headers, and cookies and allows customization through its constructor. The method attribute represents the HTTP request method, and the response attribute will store the HTTP response after executing the request.

3.3.2 Configuration manager. The configuration manager is implemented as a Singleton class named Config. It provides a centralized point of access to various application settings, such as store_log, print, and api_key. The Config class enables the user to easily manage and modify the configurations without changing the code, making the application adaptable to different environments and requirements.

3.3.3 *Logger*. The logger is a Singleton class named `Logger` that provides a unified interface for logging messages throughout the application. It supports different log levels, such as info, warning, error, and success, allowing for better control over the logging output. The logger can also store the logs in files, following a structured directory hierarchy based on the date, using the `__getLogPath` method. In addition, the `Logger` class offers methods for clearing the screen and displaying progress bars to enhance the user experience.

3.4 Inputting the Mathematical Models

The mathematical models serve as the foundation for the creation of formulas used in the analysis of mutual funds. These models enable the calculation of various metrics, such as performance, risk-adjusted returns, and volatility, to help investors make informed decisions. The models are designed to be extensible, allowing for the addition of new formulas and metrics as needed. After creating all the formulas in Jupyter Notebook, we changed their format to fit into Python system. After creating the databases by the use of the Returns of the Funds, the Benchmarks and the Risk Free Rates, we linked these databases to each fund to use in the calculations. These three databases became our main data points throughout our whole calculation process. We will talk about these more in detail in “Working with Data” part of the Methodology part of this thesis. Some examples of the implementations can be seen in the figures below.

```

from models.Math.Covariance_Math import CovarianceMath
from models.Math.math_interface import IMath
import numpy as np
from typing import List
from datetime import datetime
from lib.refax_repo.lib import CustomDate, Info
import statistics
import numpy as np
from numpy import sin
from models.ra_data_response import RaDataResponse
from models.ra_data_response import RNDDataResponse
from models.Math.Covariance_Math import CovarianceMath

class PearsonCorrelation(Math):
    """(Parameter) fund_code: Any | None"""

    def __init__(self, start_date: str, fund_code=None, end_date: str = None) -> None:
        super().__init__()
        self.start_date = start_date
        self.fund_code = fund_code
        self.end_date = end_date

    def calculate(self):
        data = RaDataResponse().whereDateTS("TARIM", ">=", [self.start_date]) \
            .whereDateTS("TARIM", "<=", [self.end_date]) \
            .where("FONDODU", "=", [self.fund_code]) \
            .get()

        if (data.count() > 2):
            return 0.8

        delta_x = statistics.stdev(data.toFloatArray("KAZANC"))
        data2 = RaDataResponse().whereDateTS("TARIM", ">=", [self.start_date]) \
            .whereDateTS("TARIM", "<=", [self.end_date]) \
            .where("FONDODU", "=", [self.fund_code]) \
            .get()

        if (data.count() > 2):
            return 0.4

        delta_y = statistics.stdev(data2.toFloatArray("KAZANC"))

        values = data.toFloatArray("KAZANC")
        values2 = data2.toFloatArray("KAZANC")
        Cov = CovarianceMath(self.start_date, self.fund_code, self.end_date)
        PearsonCor = Cov.calculate() / (delta_x * delta_y)
        return float(PearsonCor)

```

Figure 9. Covariance Python Formula Creation

```

from datetime import datetime
import pandas as pd
import statistics
from models.ra_data_response import RaDataResponse

import math
# ...

class MyDrawdown:

    def __init__(self, start_date: str, end_date: str, fund_code: str):
        self.start_date = start_date
        self.end_date = end_date
        self.fund_code = fund_code

    def calculate(self):
        data = RaDataResponse().whereDateTS("TARIM", ">=", [self.start_date]) \
            .whereDateTS("TARIM", "<=", [self.end_date]) \
            .where("FONDODU", "=", [self.fund_code]) \
            .get()

        values = pd.DataFrame(data.toFloatArray("KAZANC"))

        # Calculate cumulative returns
        cumulative_returns = (1 + values.pct_change()).cumprod() - 1

        # Calculate drawdowns
        max_cumulative_return = cumulative_returns.max()[0]
        peak_index = cumulative_returns.idxmax()[0]
        sub_cumulative_returns = cumulative_returns[peak_index:]
        if len(sub_cumulative_returns) > 0:
            trough_index = sub_cumulative_returns.idxmin()[0]
            drawdown = (max_cumulative_return - sub_cumulative_returns.iloc[-1][0]) / max_cumulative_return
            drawdowns = [drawdown]
        while trough_index < len(cumulative_returns) - 1:
            max_cumulative_return = cumulative_returns[trough_index:].max()[0]
            peak_index = cumulative_returns[trough_index:].idxmax()[0]
            sub_cumulative_returns = cumulative_returns[peak_index:]
            if len(sub_cumulative_returns) > 0:
                trough_index = sub_cumulative_returns.idxmin()[0]
                drawdown = (max_cumulative_return - sub_cumulative_returns.iloc[-1][0]) / max_cumulative_return
                drawdowns.append(drawdown)
            else:
                break
        else:
            drawdowns = []

        return drawdowns

```

Figure 10. Drawdown Python Formula Creation

```

from models.Math.Math_Interface import IMath
import numpy as np
from typing import *
from datetime import datetime
from lihs.tefas_repo.lib import FundNames, Tefas
from models.ra_data_response import RaDataResponse
from models.rf_data import RFData
from models.ra_data_response import RaDataResponse
from models.rf_data_response import RfDataResponse

class KendallCorrelation(IMath):

    def __init__(self, start_date: str, fund_code=None, end_date: str = None) -> None:
        super().__init__()
        self.start_date = start_date
        self.fund_code = fund_code
        self.end_date = end_date

    def calculate(self):
        n = np.shape(0)
        data = RaDataResponse().whereDateTS("TARIH", ">", {self.start_date}) \
            .whereDateTS("TARIH", "<=", {self.end_date}) \
            .where("FONKODU", "=", {self.fund_code}) \
            .get()
        data2 = RfData().whereDateTS("TARIH", ">", {self.start_date}) \
            .whereDateTS("TARIH", "<=", {self.end_date}).get()
        data3 = RfDataResponse().whereDateTS("TARIH", ">", {self.start_date}) \
            .whereDateTS("TARIH", "<=", {self.end_date}) \
            .where("FONKODU", "=", {self.fund_code}) \
            .get()

        Ra = data.toFloutArray("KAZANCI")
        Rf = data2.toFloutArray("RF")
        Rb = data3.toFloutArray("KAZANCI")
        a = []
        b = []
        for (i,x) in zip(Ra,Rf):
            a.append(i-x)

        for (i,x) in zip(Rb,Rf):
            b.append(i-x)

        Nc=0
        Nd=0

        for (i,x) in zip(a,b):
            if i>x:
                Nc+=1
            elif i<x:
                Nd+=1

        KendallCorrelation=(2*(Nc-Nd))/(n*(n-1))
        return float(KendallCorrelation.doit().subs(n, len(Ra)-1))

```

Figure 11. Kendall Correlation Python Formula Creation

By combining these components and working with Risk Active, we created a robust and flexible application for mutual fund analysis using Python. This approach allows for the efficient extraction and processing of data from the Turkish market, the implementation of customizable configurations, and the creation of various formulas to assess the performance of mutual funds.

3.5 Working with Data

Once we had set up the necessary coding systems in Python to retrieve the data, we began the retrieval process. We selected the period between 2020 and 2022 for our data analysis and called the data into our system. Initially, we encountered the

challenge of the slow retrieval process, which took 3 to 4 days for each call. Despite this, we managed to pull all the data into our system.

However, after working with the data, we quickly discovered that if there was a null value in one of the funds, the entire day's values were discarded. This resulted in a considerable amount of missing data in the system. Our first attempt to address this issue involved introducing a false real and non-real attribute to bypass the problem. We downloaded the data once again and recreated the return data. Unfortunately, we soon realized that the Risk Active system kept crashing while we were downloading our data, causing the system to treat all data as non-real.

Given that this was an issue with Risk Active's systems, we opted to manually intervene each time the system crashed. We would stop the program, delete the fund/benchmark for that day, run the system for that day, jump to another day, include the fund/benchmark again, and run the system again. We repeated this process for two months, yet there was still a significant amount of missing data.

To work with the available data, we created calculation systems for the return of funds, benchmarks, and risk-free rates. We initially planned to calculate the returns on a daily basis using the formula $((P[t]-P[t-1])/P[t-1])$. However, we faced challenges due to the absence of values in the TEFAS system on weekends and holidays, causing our system to crash.

To address this issue, we first attempted to move Friday values onto weekends, but the system continued to crash. We then introduced a shift day of up to 3 days, which meant that if the system found a value in the first day, it shifted up to 3 days back until it found a value. However, this approach did not account for longer holidays, and we couldn't introduce holidays manually into the system.

Additionally, the data retrieval issues led to numerous blank values and non-real values in the system. Even with a shift value of 7 or 15 days, we couldn't resolve the crashing problem due to the large number of missing values. Ultimately, we decided that calculating monthly returns provided the best possible results given the data constraints we faced.

After trying several solutions to address the data retrieval and calculation challenges, we realized that the most effective approach was to adjust the return calculation method. Instead of daily or weekly return calculations, we chose to

[illegible]

```

Veri bulmak için bütün yollar denendi
ama veri bulunamadığı için None
döndürüyoruz.
***
return None

'''
PSeccoçlardan ilkinin değeri aktörse
formül patl1mr e y2zden
bu K1son eklendi
'''
if self.model.firat().FIYAT==1:
    return None

P = IndexedBase('P')
t = symp.symbols('t', cls=symp.Ids)

Ra = ((P[t]-P[t-1])/(P[t-1]))

values1 = self.model.toFloatArray('FIYAT')
self.response = float(Ra.subs(t, 1).subs(
    {P[t], values1[t]} for t in range(len(values1))
))
})
return self.response

def __convertMonthFormat(self) -> bool:
    first_value = None
    second_value = None

    for i in range(0, self.last_chance_previous_day_limit-1):
        self.start_date = self.start_date +timedelta(days=i)
        self.end_date = self.start_date +timedelta(days=self.shift)
        first_value = self.__findFirst()
        second_value = TefasResponse().whereDateTS(
            'TARİH', '=', self.end_date).where('FONKODU', '=', self.fund_code).first()
        if not first_value == None and not second_value == None:
            break

    self.model = DBCollection(
        second_value,
        first_value
    )

    return False if first_value == None or second_value == None else True

def __findFirst(self):
    for i in range(0, self.start_date_previous_day_limit+1):

```

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```

        self.model = DBCollection([
            second_value,
            first_value
        ])

        return False if first_value == None or second_value == None else True

    def __findFirst(self):
        for i in range(0, self.standart_previous_day_limit+1):
            self.start_date = self.start_date-timedelta(days=i)
            response = TefasResponse().whereDateTS(
                'TARIH', '=', self.start_date).where('FONKODU', '=', {self.fund_code}).first()
            if not response == None:
                return response
        return None

    def print(self):
        if self.response == None:
            return
        print("day_range: [ {}/{} ] => [value: {}, week_number: {}]*.format(
            self.start_date,
            self.end_date,
            self.response,
            self.start_date.isocalendar()[1]))

    def startDateToTimestamp(self) -> int:
        return TefasResponse().dateToTimestamp(self.start_date)

    def endDateToTimestamp(self) -> int:
        return TefasResponse().dateToTimestamp(self.end_date)

```

Figure 14. Fund Return Python Calculation Part 3

Following the calculation of the return of the funds, we utilized the Ra_Data_Response code to create our first database. This code enabled us to build a database within our Finance CodeBook system, where we could access each fund's return on their specific dates for use in our calculations. From that point onwards, this database served as the foundation for all calculations performed under our Math module. By establishing a centralized database of returns, we were able to streamline our analysis and ensure consistency across all calculations in the methodology.

For calculating the return of benchmark values, we employed a different and more complex method. First, we had a comprehensive Excel file containing the fund's corresponding benchmarks, their ratios for specific dates, and the date ranges for these ratios. In order to efficiently process this information, we created a new code called BenchmarkExcel, which extracted all the necessary data from this extensive Excel file. This process facilitated the identification of the appropriate ratios and benchmarks for each fund.

As a second step, we connected to Risk Active's system to obtain benchmark prices for the relevant dates. This integration was crucial in ensuring that we had accurate and up-to-date benchmark pricing information for our calculations.

Using a new code called `Benchmark_value`, we multiplied each ratio and the benchmark values for the relevant fund, and then created a new database called `Benchmark_values`. This database was subsequently used in calculating the return of benchmarks, allowing us to streamline the process and maintain an organized structure for handling these calculations.

However, the amount of data available for benchmarks was even more limited than for funds. Despite using a monthly calculation for their returns, the three years of calculated returns only amounted to a year's worth of values. This posed a significant challenge in ensuring accurate and complete benchmark return calculations.

Later on, we received additional data in the form of an Excel file from the Risk Active team. We spent two weeks adjusting the entire data retrieval process to incorporate this new information, hoping it would improve the completeness of our benchmark return data. Unfortunately, the final amount of data did not change significantly, so we continued with the original option of an automatic updating system. Following the calculation of the return of the benchmarks, we utilized the `Rb_Data_Response` code to create second first database. This code enabled us to build a database within our Finance CodeBook system, where we could access each benchmark's return on their specific dates for use in our calculations. From that point onwards, this database served as a foundation for all calculations performed under our Math module. By establishing a centralized database of the benchmark returns, we were able to streamline our analysis and ensure consistency across all calculations in the methodology. The final Benchmark Return codes can be seen in the figures below.

```

from database.orm_models.db_collection import DBCollection
from models.Math.math_interface import IMath
import sympy as sp
from sympy import *
from datetime import datetime, timedelta

from models.benchmark_value import BenchmarkValue

You, 4 seconds ago | 2 authors (Aras Taşkın and others)
class RbCalculator(IMath):

    def __init__(self, start_date: datetime, fund_code=None, end_date: str = None) → None:
        super().__init__()
        """
        Tarihi klonlamak için üzerine self.gün ekliyorum
        çağırıldığı yerdeki tarihi manipüle etmesin diye
        """
        self.start_date = datetime + start_date + timedelta(days=0)
        self.fund_code = fund_code
        self.end_date = end_date
        self.model = None
        self.shift = 30
        self.response = None
        """
        [standart_previous_day_limit] start_date değerinin
        bulunduğu günden itibaren kaç gün geri gidebileceğini
        kısttlar.
        """
        self.standart_previous_day_limit = 3
        """
        [last_chance_previous_day_limit] değeri
        son bir şans daha vermek için ön kaydırma
        yaparak tekrar deneme limiti
        """
        self.last_chance_previous_day_limit = 3

    def calculate(self):
        """
        (Bugunun fiyatı - Geçen Haftanın fiyatı) / Geçen Haftanın fiyatı

        PS: Sonuç döndürme garantisi yoktur, null
        değer döndürebilir.
        """

```

Figure 15. Benchmark Return Python Calculation Part 1

```

if not self.__convertWeekFormat():
    """
    Veri bulmak için bütün yollar denendi
    ama veri bulunamadığı için None
    döndürüyoruz.
    """
    return None

"""
P5: Gelen sonuçlardan ilkinin değeri self.first
formül patlıyor o yüzden burası ekleniyor.
"""
if self.model.first().FIYAT == 0:
    return None

P = IndexedBase('P')
t = snp.symbols('t', c[s:snp.Idx])

Rb = ((P[t]-P[t-1])/P[t-1])

values1 = self.model.toFloatArray('FIYAT')
self.response = float(Rb.subs(t, 1).subs(
    [
        (P[t], values1[t]) for t in range(len(values1))
    ]
))
return self.response

def __convertWeekFormat(self) -> bool:
    first_value = None
    second_value = None

    for i in range(0, self.last_chance_previous_days+1):
        self.start_date = self.start_date-timedelta(days=float(i))
        self.end_date = self.start_date-timedelta(days=self.shift)
        first_value = self.__findFirst()
        second_value = self.findSecondValue()
        if not first_value == None and not second_value == None:
            break

    self.model = DBCollection([
        second_value,
        first_value
    ])

    return False if first_value == None or second_value == None else True

```

Figure 16. Benchmark Return Python Calculation Part 2

```

'''
def __findFirst(self):
    for i in range(0, self.standart_previous_day_limit+1):
        self.start_date = self.start_date - timedelta(days=i)
        response = BenchmarkValue().whereDateTS(
            'TARIH', '=', self.start_date).where('FONKODU', '=', {self.fund_code}).first()
        if not response == None:
            return response
    return None

def findSecondValue(self):
    end = self.end_date

    for i in range(0, self.last_chance_previous_day_limit):
        d = BenchmarkValue().whereDateTS(
            'TARIH', '=', (end - timedelta(days=i))).first()

        if not d == None:
            return d

    return None

def print(self):
    if self.response == None:
        return
    print("day_range: [ {0}/{1} ] => [value: {2}, week_number: {3}].format(
        self.start_date,
        self.end_date,
        self.response,
        self.start_date.isocalendar()[1])

def startDateToTimestamp(self) -> int:
    return BenchmarkValue().dateToTimestamp(self.start_date)

def endDateToTimestamp(self) -> int:
    return BenchmarkValue().dateToTimestamp(self.end_date)

```

Figure 17. Benchmark Return Python Calculation Part 3

In the methodology for calculating the Risk-Free Rate Return, we first needed to index the Yield Curve Values. To accomplish this, we created a class called `Rf_endexleme`. We initialized the first value of the index to 100 as a base value for comparison purposes. Using the formula “ $\text{prev_val} * (1 + (\text{result.O_N} / 36500 * \text{delta}))$ ”, we iterated through the rest of the data across the date range.

Each indexed value was then stored in the `endex_values` database. With the indexed Yield Curve Values in hand, we proceeded to calculate the Returns of the Risk-Free Rates. To maintain consistency in our analysis, we also calculated Risk-Free Returns on a monthly basis, similar to the calculations for fund and benchmark returns. This approach ensured a balanced and comparable evaluation of the returns across the different components of our study. Following the calculation of the return of the benchmarks, we utilized the `Rf_Data_Response` code to create third first database. This code enabled us to build a database within our Finance CodeBook system, where we could access each Risk Free Rate’s return on their specific dates

for use in our calculations. From that point onwards, this database served as a foundation for all calculations performed under our Math module. By establishing a centralized database of the Risk-Free returns, we were able to streamline our analysis and ensure consistency across all calculations in the methodology. The final Risk-Free Return codes can be seen in the figures below.

```
class Index(IMath):
    def __init__(self, start_date: str = "", end_date: str = None) → None:
        super().__init__()
        self.start_date = start_date
        self.end_date = end_date

    def calculate(self):
        start_date = datetime.strptime(self.start_date, "%d.%m.%Y")
        end_date = datetime.strptime(self.end_date, "%d.%m.%Y")

        day_diff = (end_date - start_date).days
        endex_values = []
        prev_val = 0
        prev_date = None
        for i in range(0, day_diff+1):
            curr_date = start_date + timedelta(days=i)
            if i == 0:
                endex_values.append(100)
                self.__store(curr_date, 100)
                prev_val = 100
                prev_date = curr_date + timedelta(days=0)
                for r in range(0, 5):
                    prev_date = curr_date - timedelta(days=r)
                    k = YieldCurveDataResponse().whereDateTS("TARIH", "=", prev_date).first()
                    if not k == None:
                        break
                    continue
                result = YieldCurveDataResponse().whereDateTS("TARIH", "=", curr_date).first()
                if result == None:
                    continue
                delta = (curr_date - prev_date).days
                res = prev_val * (1 + (result.O_N / 36500 * delta))
                endex_values.append(res)
                self.__store(curr_date, res)
                prev_val = res
                prev_date = curr_date + timedelta(days=0)
            else:
                continue

        return endex_values

    def __store(self, date: datetime, value: float):
        exist: YieldIndex = YieldIndex().whereDateTS(
            "TARIH", "=", date).first()
        if not exist == None:
            exist.delete()

        new_date = YieldIndex()
        new_date.TARIH = new_date.dateToTimestamp(date)
        new_date.YIELD = value
        new_date.store()
```

Figure 18. Risk Free Endexing Code System

```

class RfCalculator(IMath):

    def __init__(self, start_date: datetime, end_date: str = None) → None:
        super().__init__()
        self.start_date: datetime = start_date+timedelta(days=0)
        self.end_date = end_date
        self.model = None
        self.shift = 7
        self.response = None
        self.standart_previous_day_limit = 4
        self.last_chance_previous_day_limit = 20
        self.__logger = Logger.getInstance()

    def calculate(self):
        if self.start_date.day == 30:
            print("sdasd")

        if not self.__convertWeekFormat():
            return None

        if self.model.first().YIELD == 0:
            return None

        P = IndexedBase('P')
        t = smp.symbols('t', cls=smp.Idx)

        Ra = ((P[t]-P[t-1])/P[t-1])

        values1 = self.model.toFloatArray('YIELD')
        self.response = Float(Ra.subs(t, 1).subs(
            [
                (P[t], values1[t]) for t in range(len(values1))
            ]
        ))

        return self.response

    def __convertWeekFormat(self) → bool:
        first_value = None
        second_value = None

        for i in range(0, self.last_chance_previous_day_limit+1):
            if i > 0:
                self.start_date = self.start_date-timedelta(days=1)
                self.end_date = self.start_date-timedelta(days=self.shift)
                first_value = self.__findFirst()
                if first_value == None:
                    self.__logger.error("First value empty ( {0} )".format(
                        self.__logger.dateToStr(self.start_date)))
                    continue

                # SECOND
                second_value = self.findSecondValue()
                if not first_value == None and not second_value == None:
                    break

```

Figure 19. Risk Free Return Python Calculation Part 1

```

        self.__logger.error(
            "Unfortunately, I couldn't find the value for the second day ( {0} - {1} ). I'm going to try day shifting.".format(
                self.__logger.dateToStr(self.start_date),
                self.__logger.dateToStr(self.end_date)
            )
        )

    self.model = DBCollection([
        second_value,
        first_value
    ])

    return False if first_value == None or second_value == None else True

def findSecondValue(self):
    end = self.end_date

    for i in range(0, self.last_chance_previous_day_limit):
        d = YieldIndex().whereDateTS(
            'TARIIM', '=', (end - timedelta(days=i)).first()
        )

        if not d == None:
            return d

    return None

def __findFirst(self):
    for i in range(0, (self.standart_previous_day_limit+1)):
        if i == 0:
            self.start_date = self.start_date - timedelta(days=i)
            self.__logger.info("RfCalculator: I'm looking for the first day value: {0}".format(
                self.__logger.dateToStr(self.start_date)
            ))
            response = YieldIndex().whereDateTS(
                'TARIIM', '=', (self.start_date).first()
            )
            if not response == None:
                self.__logger.success(
                    "I have good news, I found its value on the first day ( {0} ). If I find value for the second day I will continue".format(
                        self.__logger.dateToStr(self.start_date)
                    )
                )
                return response

    return None

def print(self):
    if self.response == None:
        return
    print("day_range: [ {0}/{1} ] == [value: {2}], week_number: {3}.".format(
        self.start_date,
        self.end_date,
        self.response,
        self.start_date.isocalendar()[1]
    ))

def startDateToTimestamp(self) -> int:
    return TefasResponse().dateToTimestamp(self.start_date)

```

Figure 20. Risk Free Return Calculation Part 2

3.6 Running the System and Creation of Tables

After creating the databases for the funds, benchmarks, and risk-free rates, and updating the performance measures to fit into the Python interface, we ended up with 89 different mathematical financial calculation methods within our application. These methods were applied to 1,122 different funds, which included all the funds in the Risk Active's fund system. They iterated through all the dates and values between the given date period. An example of some of the funds used in our system can be seen in the figure below.

FONKODU	FONUNVAN
AAK	ATA PORTFÖY ÇOKLU VARLIK DEĞİŞKEN FON
AAL	ATA PORTFÖY PARA PİYASASI FONU
AAS	ATA PORTFÖY FON SEPETİ SERBEST FONU
AAV	ATA PORTFÖY İKİNCİ HİSSE SENEDİ FONU (HİSSE SENEDİ YOĞUN FON)
ABU	AK PORTFÖY BİREBİR BANKACILIK DEĞİŞKEN ÖZEL FON
ACC	İSTANBUL PORTFÖY DÖRDÜNCÜ HİSSE SENEDİ FONU (HİSSE SENEDİ YOĞUN)
ACD	İSTANBUL PORTFÖY İKİNCİ DEĞİŞKEN FON
ACK	İSTANBUL PORTFÖY HİSSE SENEDİ FONU(HİSSE SENEDİ YOĞUN FON)
ACN	İSTANBUL PORTFÖY LİDYA SERBEST (DÖVİZ) FON
ACU	İSTANBUL PORTFÖY URARTU SERBEST (DÖVİZ) FON
ACZ	İSTANBUL PORTFÖY HİTİT SERBEST FON
ADE	AK PORTFÖY DEĞİŞKEN FON
ADP	AK PORTFÖY BİST BANKA ENDEKSİ HİSSE SENEDİ FONU (HİSSE SENEDİ YOĞUN FON)
AED	ATA PORTFÖY BİRİNCİ DEĞİŞKEN FON
AES	AK PORTFÖY PETROL YABANCI BYF FON SEPETİ FONU
AFA	AK PORTFÖY AMERİKA YABANCI HİSSE SENEDİ FONU
AFO	AK PORTFÖY ALTIN FONU
AFS	AK PORTFÖY SAĞLIK SEKTÖRÜ YABANCI HİSSE SENEDİ FONU
AFT	AK PORTFÖY YENİ TEKNOLOJİLER YABANCI HİSSE SENEDİ FONU
AFV	AK PORTFÖY AVRUPA YABANCI HİSSE SENEDİ FONU
AGC	AK PORTFÖY İKİNCİ DEĞİŞKEN FON
AHI	ATLAS PORTFÖY BİRİNCİ HİSSE SENEDİ FONU(HİSSE SENEDİ YOĞUN)
AHN	ATLAS PORTFÖY SERBEST(DÖVİZ)FON
AHU	ATLAS PORTFÖY BİRİNCİ ÖZEL SEKTÖR BORÇLANMA ARAÇLARI FONU
AHV	AZİMUT PYŞ DENGELİ SERBEST FON
AHZ	AZİMUT PYŞ ATAK SERBEST FON
AIG	AZİMUT PORTFÖY İA SERBEST ÖZEL FON
AIH	AK PORTFÖY RTH SERBEST ÖZEL FON
AII	AZİMUT PORTFÖY ÇINAR SERBEST (DÖVİZ) ÖZEL FON
AIM	AK PORTFÖY MİMKA SERBEST ÖZEL FON
AIR	AZİMUT PORTFÖY ESİN SERBEST (DÖVİZ) ÖZEL FON
AIS	AK PORTFÖY KİRA SERTİFİKALARI KATILIM FONU
AJE	AK PORTFÖY ÜÇÜNCÜ SERBEST (DÖVİZ) FON

Figure 21. Example of funds used in the system

We decided to calculate all of our performance measures on a yearly basis and then shift one month back and calculate them on a yearly basis again, until we had 12 ratings at hand. This approach allowed us to utilize all the data at hand. In order to iterate through all the funds and obtain an Excel sheet of the returns of all the

performance measures, we realized that we had to modify the coding system once more. Some examples to the updated versions of the performance measures can be seen in the figures below.

```
from models.Math.math_interface import IMath
import sympy as sm
from sympy import +
from datetime import datetime
from libs.tefas_repo_lib import FundNames, Tefas
import statistics
import numpy as np
from models.ra_data_response import RaDataResponse
from models.rb_data_response import RbDataResponse
from models.Math.Covariance_Ra_Rb import CovarianceRaRb
from models.rb_data_response import RbDataResponse
from models.ra_data_response import RaDataResponse
from libs.tefas_repo_lib import TefasResponse
from prettytable import PrettyTable
import numpy as np
import pandas as pd
import xlswriter

You, 6 seconds ago | 1 author (You)
class BetaCoKurtosis(IMath):

    def __init__(self, start_date: str="", fund_code=None, end_date: str = None) → None:
        super().__init__()
        self.start_date = start_date
        self.fund_code = fund_code
        self.end_date = end_date

    def __init__(self, start_date: str="", fund_code=None, end_date: str = None) → None:
        super().__init__()
        self.start_date = start_date

        self.end_date = end_date

    def calculate(self):
        fund_codes = TefasResponse().getFundNames()
        BetCoKurtosis = {}
        date_range = pd.date_range(self.start_date, self.end_date, freq='D')
```

Figure 22. Updated BetaCoKurtosis Calculator Part 1

```

for code in fund_codes:
    data = RaDataResponse().whereDateTS("TARİH", ">=", {self.start_date}) \
        .whereDateTS("TARİH", "<=", {self.end_date}) \
        .where("FONKODU", "=", {code}) \
        .get()
    ra = data.toFloatArray("KAZANC")
    asset_excess_returns = ra - np.mean(ra)

    data2 = RbDataResponse().whereDateTS("TARİH", ">=", {self.start_date}) \
        .whereDateTS("TARİH", "<=", {self.end_date}) \
        .where("FONKODU", "=", {code}) \
        .get()
    rb = data2.toFloatArray("KAZANC")
    benchmark_excess_returns = rb - np.mean(rb)

    if len(ra) > 0 and len(rb) > 0:
        min_length = min(len(asset_excess_returns), len(benchmark_excess_returns))
        asset_excess_returns = asset_excess_returns[:min_length]
        benchmark_excess_returns = benchmark_excess_returns[:min_length]

        # Calculate covariance
        covariance = np.cov(asset_excess_returns, benchmark_excess_returns, ddof=1)[0][1]

        # Calculate beta
        beta = covariance / np.var(rb)

        # Calculate co-kurtosis
        co_kurtosis = np.mean(asset_excess_returns**2 * benchmark_excess_returns**2) / \
            (np.std(ra, ddof=1)**2 * np.std(rb, ddof=1)**2 * beta**2)
        BetCoKurtosis[code] = co_kurtosis
        print(f"Annualized average geometric return for fund code {code}: {BetCoKurtosis[code]}")
    else:
        BetCoKurtosis[code] = np.nan

return BetCoKurtosis

def create_table(self, results):
    table = PrettyTable()
    table.field_names = ["Fund Code", "co_kurtosis"]
    for code, co_kurtosis in results.items():
        table.add_row([code, co_kurtosis])
    return table

def export_to_excel(self, results, co_kurt12):
    workbook = xlswriter.Workbook(co_kurt12)
    worksheet = workbook.add_worksheet()

    # write header row
    header_format = workbook.add_format({'bold': True, 'align': 'center'})
    worksheet.write(0, 0, "Fund Code", header_format)
    worksheet.write(0, 1, "co_kurtosis", header_format)

    # write data rows
    row = 1
    for code, result_value in results.items():
        worksheet.write(row, 0, code)

```

Figure 23. Updated BetaCoKurtosis Calculator Part 2

```

try:
    if np.isnan(float(result_value)):
        worksheet.write(row, 1, "N/A")
    else:
        # Format the value with 18 decimal places
        formatted_value = format(float(result_value), '.18f')
        worksheet.write(row, 1, formatted_value)
except (ValueError, TypeError):
    worksheet.write(row, 1, "Invalid Value")
row += 1

workbook.close()

```

Figure 24. Updated BetaCoKurtosis Calculator Part 3

```

from models.Math.math_interface import IMath
import sympy as sm
from sympy import *
from datetime import datetime
from libs.tefas_repo_lib import FundNames, Tefas
from models.ra_data_response import RaDataResponse
from prettytable import PrettyTable
import xlswriter
from libs.tefas_repo_lib import TefasResponse
import numpy as np
import pandas as pd  # You, last month + yenilik
You, 1 second ago | 1 author (You)
class ExcessKurtosis(IMath):

    def __init__(self, start_date: str="", end_date: str = None) → None:
        super().__init__()
        self.start_date = start_date
        self.end_date = end_date

    def calculate(self):
        fund_codes = TefasResponse().getFundNames()

        ExcessKurt = {}
        Ra = IndexedBase('Ra')
        i, n = sm.symbols('i n', integer=True)
        mean_ra_values={}
        var_ra={}

        for code in fund_codes:
            ra_data = RaDataResponse().whereDateTS("TARİH", "≥", {self.start_date}) \
                .whereDateTS("TARİH", "≤", {self.end_date}) \
                .where("FONKODU", "=", {code}) \
                .get()

            if ra_data.count()>0:
                mean_ra = np.mean(ra_data.toFloatArray("KAZANC"))
                mean_ra_values[code] = mean_ra
            else:
                mean_ra_values[code]=np.nan

        for code in fund_codes:
            ra_data = RaDataResponse().whereDateTS("TARİH", "≥", {self.start_date}) \
                .whereDateTS("TARİH", "≤", {self.end_date}) \
                .where("FONKODU", "=", {code}) \
                .get()

            values=ra_data.toFloatArray("KAZANC")

            squared_diffs = [(x - mean_ra_values[code]) ** 2 for x in values]
            var_ra [code]= sum(squared_diffs) / (len(values) - 1)

        for code in fund_codes:
            data = RaDataResponse().whereDateTS("TARİH", "≥", {self.start_date}) \
                .whereDateTS("TARİH", "≤", {self.end_date}) \
                .where("FONKODU", "=", {code}) \
                .get()

            if data.count() > 0:
                values = data.toFloatArray("KAZANC")

```

Figure 25. Updated Excess Kurtosis Calculator Part 1

```

for code in fund_codes:
    data = RaDataResponse().whereDateTS("TARIH", ">=", (self.start_date)) \
        .whereDateTS("TARIH", "<=", (self.end_date)) \
        .where("FONKODU", "=", (code)) \
        .get()
    if data.count() > 0:
        values = data.toFloatArray("RAZANC")

        # calculate the excess kurtosis of Ra
        excess_kurtosis = sep.Sum((Ra[i] - mean_ra_values[code]) ** 4 * (n ** 2), [i, 0, n-1]) / ((n - 3) * (var_ra [code] * (n - 1) ** 2))
        excess_kurtosis = excess_kurtosis.subs(n, len(values)-1).subs([i, a] for a in range(len(values)-1))
        .doit().subs([(Ra[i], values[i]) for i in range(len(values))])

        ExcessKurt[code] = abs(excess_kurtosis)

        print(f"Excess kurtosis for fund code {code}: {ExcessKurt[code]}")
    else:
        ExcessKurt[code] = np.nan

return ExcessKurt

def create_table(self, results):
    table = PrettyTable()
    table.field_names = ["Fund Code", "Excess Kurtosis"]
    for code, ExcessKurtosis in results.items():
        table.add_row([code, ExcessKurtosis])
    return table

def export_to_excel(self, results, ExcessKurt2):
    df = pd.DataFrame.from_dict(results, orient="index")
    df.index.name = "Fund Code"
    df.columns = ["ExcessKurtosis"]
    df.replace([np.inf, -np.inf], np.nan, inplace=True) # replace infinite values with nan
    df.fillna(value="nan", inplace=True) # replace nan values with the string "nan"
    writer = pd.ExcelWriter(ExcessKurt2+".xlsx")
    df.to_excel(writer, sheet_name="Sheet1")
    writer.save()
    print(f"ExcessKurtosis is created successfully!")

```

Figure 26. Updated Excess Kurtosis Calculator Part 2

Upon running the system for all the available fund codes, we discovered that some of our performance measures had lost their meaningfulness due to the lack of data during specific dates or from overall lack of reach of data. To avoid miscalculations, we discarded these performance measures from the final selection which left us with 70 performance measures in our final ranking system.

We also found that not all of the 1,122 funds had values during our specified time spans, or we could not access their values, rendering them obsolete. The total number of remaining funds will be discussed in more detail in the Ranking of the Funds section of the methodology.

Our dataset extended until 02.02.2022, so we decided to start our yearly calculations from the date span of “01.01.2022” to “01.01.2021” and shift month-by-month until we reached “01.02.2020”-“01.03.2021” so we have 12 ratings in total that span a year. Some examples of our first calculations of our mathematical models and their resulting excel sheets for the date range “01.01.2022” to “01.01.2021” can be seen in figures below. Due to the considerable amount of missing data, there are

many N/A and NaN values. However, these values will be addressed and calculated accordingly in the ranking section of the methodology.

Fund Code	AnnualizedAverageGeometricReturn										
AAK	-0,86684	ARF	0,213845	DCD	N/A	DVT	N/A	FSF	0,20232	GFD	N/A
AAL	0,198182	ARL	0,265319	DCE	N/A	DVU	N/A	FSK	0,187194	GFE	N/A
AAS	107,6926	ARM	0,323738	DCP	0,608562	DVZ	N/A	FUA	N/A	GFF	N/A
AAV	166,8856	ARP	0,568151	DCV	N/A	DYJ	N/A	FUB	0,400651	GFG	N/A
ABG	N/A	ATJ	0,697868	DDA	0,434487	DYN	N/A	FUM	N/A	GFK	N/A
ABU	0,179403	AUT	115,5354	DDC	0,190421	DZE	0,657835	FUP	1,267973	GFL	0,693988
AC1	N/A	AVC	22,61675	DDE	0,500373	DZG	0,346731	FVL	N/A	GFN	N/A
AC2	N/A	AVT	0,180959	DDF	0,1722	DZM	0,446706	FVS	0,728032	GFO	N/A
AC3	N/A	AVZ	0,465192	DDP	0,496318	DZT	-0,01568	FYA	0,915417	GFT	N/A
AC4	N/A	AYA	14,71814	DDS	0,171566	EBD	0,441365	FYB	0,430717	GFV	N/A
ACS	N/A	AYR	0,19638	DFC	N/A	EC2	0,598077	FYD	0,811335	GFY	N/A
ACC	0,296508	AZF	0,241194	DFD	N/A	ECA	0,448769	FYF	0,15421	GGB	-1
ACD	0,723362	AZJ	0,27393	DFI	N/A	ECB	0,198386	FYG	0,332048	GGC	0,21835
ACK	0,489306	AZV	0,514405	DGH	120,2731	ECT	0,17434	FYH	0,407868	GGK	0,232844
ACN	0,572681	AZZ	N/A	DHJ	N/A	ECV	0,179681	FYI	0,30993	GGL	0,394933
ACU	0,386596	BDC	N/A	DHM	N/A	EIB	0,266293	FYJ	N/A	GGM	0,224505
ACZ	0,39424	BGP	0,201424	DHS	N/A	EIC	0,354569	FYM	0,385112	GGN	N/A
ADE	0,182081	BJD	0,32124	DKD	0,303121	EID	0,60225	FYO	0,172574	GGP	0,573359
ADP	0,370862	BJO	0,071224	DKS	N/A	EIL	0,207364	FYT	0,166756	GGR	0,415789
AED	1472,17	BRG	0,024968	DKV	N/A	EJG	0,299995	FYV	N/A	GGV	-1
AES	1,79579	BVB	N/A	DLD	N/A	EKF	0,203731	FYZ	N/A	GGZ	0,261151
AFA	0,879376	BVC	N/A	DLG	N/A	ELZ	0,318606	FZJ	0,040156	GHS	0,762952
AFO	0,261383	BVM	N/A	DLY	0,194479	ESG	0,242346	FZP	0,320267	GJA	0,325306
AFS	1,083575	BVT	N/A	DMG	N/A	EUZ	0,361748	GA1	0,204522	GJB	0,218469
AFT	0,734273	BVY	N/A	DNL	N/A	FBN	0,377773	GAC	0,200228	GJD	0,332395
AFV	0,762804	CEY	-1	DNO	1,103483	FBV	0,1121	GAE	0,566973	GJE	0,319606
AGC	0,330579	CJD	0,358665	DOA	N/A	FBZ	0,175438	GAF	0,472817	GJF	0,314699
AHI	0,786889	CJF	0,351288	DOD	N/A	FCV	0,210551	GAG	0,43572	GJH	-1
AHN	0,452811	CJG	0,323539	DOI	N/A	FDO	-1	GAH	0,236576	GJM	0,135517
AHU	0,222507	CJH	-0,05754	DOR	N/A	FDV	N/A	GAJ	0,207956	GJO	0,316454
AHV	0,323861	CTF	0,462973	DOS	0,540187	FDZ	N/A	GAK	0,302084	GJP	-0,03695
AHZ	0,413534	CTG	0,546154	DP1	N/A	FFD	0,167364	GAL	0,193933	GKF	0,01386
AIG	0,499278	CTM	0,494278	DPB	0,546431	FFH	0,292936	GAN	0,218887	GKH	N/A
AIH	-0,3727	CTP	0,406989	DPC	0,511939	FFO	0,643186	GAS	0,428796	GKK	0,41811
AIJ	0,60682	CTV	0,715081	DPE	0,566006	FFP	0,376191	GAU	0,262502	GKL	0,268377
AIM	-0,25027	CVA	N/A	DPG	0,59469	FFS	0,481639	GAV	0,19294	GKS	0,250712
AIR	1,008485	CVB	N/A	DPI	0,174601	FI3	0,12306	GBC	0,128231	GKV	N/A
AIS	0,17167	CVC	N/A	DPK	0,174453	FIS	0,193324	GBG	0,885828	GL1	0,56522
AJE	-1	CVD	N/A	DPL	0,533234	FIB	0,254459	GBL	0,205643	GLC	N/A
AJK	0,484993	CVE	N/A	DPN	0,596392	FID	0,580006	GBN	0,211301	GLG	N/A
AJL	0,504363	CVF	N/A	DPP	0,60407	FIL	0,204123	GBP	N/A	GLM	N/A
AJN	0,465339	DAC	N/A	DPT	0,935812	FIT	0,138849	GBV	0,171005	GLN	N/A
AK2	-0,03706	DAH	0,598907	DPZ	0,719644	FJB	0,349558	GBZ	N/A	GLP	0,264302
AK3	0,594287	DAI	0,599718	DRS	0,380038	FJC	0,307208	GCA	N/A	GLS	0,111309
AKE	0,418996	DAL	N/A	DSC	0,4399	FJM	0,365262	GCC	N/A	GLV	N/A
AKU	0,572138	DAS	N/A	DSD	0,377282	FJN	0,224072	GCD	N/A	GLZ	-1
ALC	0,891379	DAT	0,649692	DSP	0,291385	FJZ	0,320454	GCG	N/A	GMA	0,367671
ALE	0,191835	DAZ	0,208938	DTR	-0,05561	FNO	0,308848	GCI	N/A	GMC	N/A
AN1	0,313875	DBA	0,232629	DTV	-0,04216	FPE	0,440266	GCZ	N/A	GMD	N/A
ANL	0,197719	DBB	0,077323	DTZ	-0,06354	FPH	0,581411	GDH	N/A	GME	0,999101
ANZ	0,453486	DBG	0,863472	DUT	N/A	FPK	0,18767	GDL	-1	GMG	-0,05592
AOY	0,140553	DBH	0,449329	DVA	N/A	FPR	-0,16363	GDS	0,138698	GMJ	-0,04549
APJ	0,243395	DBK	0,189584	DVC	N/A	FPZ	0,488658	GEC	N/A	GMP	0,520345
APP	0,402963	DBP	0,262379	DVI	N/A	FRA	1,177705	GEI	0,723531	GMR	0,569525
APT	0,141141	DBZ	0,206878	DVN	N/A	FRZ	0,555316	GFA	N/A	GMV	-0,03313
ARE	0,370721	DCB	N/A	DVO	N/A	FSE	N/A	GFB	N/A	GMZ	0,733668

Figure 27. Annualized Average Geometric Return Calculation Between “01.01.2022” to “01.01.2021”

AAI	16.42418191	ABP	5.95806	BCD	nan	DVT	nan	FIP	4.415539	EPD	nan	GNR	nan	IDL	5.022527	HLR	nan
AAJ	2.34131843 <td>ABU</td> <td>8.555058<td>DCE<td>nan<th>DVU</th><td>nan<th>FIR</th><td>1.793991<th>EPF</th><td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td></td></td></td></td></td>	ABU	8.555058 <td>DCE<td>nan<th>DVU</th><td>nan<th>FIR</th><td>1.793991<th>EPF</th><td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td></td></td></td></td>	DCE <td>nan<th>DVU</th><td>nan<th>FIR</th><td>1.793991<th>EPF</th><td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td></td></td></td>	nan <th>DVU</th> <td>nan<th>FIR</th><td>1.793991<th>EPF</th><td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td></td></td>	DVU	nan <th>FIR</th> <td>1.793991<th>EPF</th><td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td></td>	FIR	1.793991 <th>EPF</th> <td>nan<th>GGI</th><td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td></td>	EPF	nan <th>GGI</th> <td>nan<th>IGM</th><td>5.144056<th>INR</th><td>nan</td></td></td>	GGI	nan <th>IGM</th> <td>5.144056<th>INR</th><td>nan</td></td>	IGM	5.144056 <th>INR</th> <td>nan</td>	INR	nan
AAK	17.1288239 <th>ABM</th> <td>3.170464<th>DCP</th><td>6.773358<th>DVZ</th><td>nan<th>FJA</th></td><td>nan<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>7.104134<th>INW</th><td>nan</td></td></td></td></td></td></td>	ABM	3.170464 <th>DCP</th> <td>6.773358<th>DVZ</th><td>nan<th>FJA</th></td><td>nan<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>7.104134<th>INW</th><td>nan</td></td></td></td></td></td>	DCP	6.773358 <th>DVZ</th> <td>nan<th>FJA</th></td> <td>nan<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>7.104134<th>INW</th><td>nan</td></td></td></td></td>	DVZ	nan <th>FJA</th>	FJA	nan <th>GGJ</th> <td>nan<th>GGN</th><td>nan<th>IGN</th><td>7.104134<th>INW</th><td>nan</td></td></td></td>	GGJ	nan <th>GGN</th> <td>nan<th>IGN</th><td>7.104134<th>INW</th><td>nan</td></td></td>	GGN	nan <th>IGN</th> <td>7.104134<th>INW</th><td>nan</td></td>	IGN	7.104134 <th>INW</th> <td>nan</td>	INW	nan
AAV	17.16876455 <th>ABP</th> <td>6.665951<th>DCV</th><td>nan<th>DVU</th><td>nan<th>FJA</th></td><td>9.940764<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>6.692812<th>INW</th><td>nan</td></td></td></td></td></td></td>	ABP	6.665951 <th>DCV</th> <td>nan<th>DVU</th><td>nan<th>FJA</th></td><td>9.940764<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>6.692812<th>INW</th><td>nan</td></td></td></td></td></td>	DCV	nan <th>DVU</th> <td>nan<th>FJA</th></td> <td>9.940764<th>GGJ</th><td>nan<th>GGN</th><td>nan<th>IGN</th><td>6.692812<th>INW</th><td>nan</td></td></td></td></td>	DVU	nan <th>FJA</th>	FJA	9.940764 <th>GGJ</th> <td>nan<th>GGN</th><td>nan<th>IGN</th><td>6.692812<th>INW</th><td>nan</td></td></td></td>	GGJ	nan <th>GGN</th> <td>nan<th>IGN</th><td>6.692812<th>INW</th><td>nan</td></td></td>	GGN	nan <th>IGN</th> <td>6.692812<th>INW</th><td>nan</td></td>	IGN	6.692812 <th>INW</th> <td>nan</td>	INW	nan
ABG	nan	ATI	8.105591 <th>DGA</th>	DGA	3.912135 <th>DVN</th> <td>nan<th>FJM</th><td>nan<th>GGI</th><td>nan<th>GGN</th><td>nan<th>IGP</th><td>6.58744<th>INW</th><td>nan</td></td></td></td></td></td>	DVN	nan <th>FJM</th> <td>nan<th>GGI</th><td>nan<th>GGN</th><td>nan<th>IGP</th><td>6.58744<th>INW</th><td>nan</td></td></td></td></td>	FJM	nan <th>GGI</th> <td>nan<th>GGN</th><td>nan<th>IGP</th><td>6.58744<th>INW</th><td>nan</td></td></td></td>	GGI	nan <th>GGN</th> <td>nan<th>IGP</th><td>6.58744<th>INW</th><td>nan</td></td></td>	GGN	nan <th>IGP</th> <td>6.58744<th>INW</th><td>nan</td></td>	IGP	6.58744 <th>INW</th> <td>nan</td>	INW	nan
ABU	3.271878131 <th>AUT</th> <td>17.10807<th>DDC</th><td>4.523398<th>DZB</th><td>3.817763<th>FPL</th><td>0.08913<th>GLI</th><td>9.2443<th>GGH</th><td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td></td></td></td></td></td>	AUT	17.10807 <th>DDC</th> <td>4.523398<th>DZB</th><td>3.817763<th>FPL</th><td>0.08913<th>GLI</th><td>9.2443<th>GGH</th><td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td></td></td></td></td>	DDC	4.523398 <th>DZB</th> <td>3.817763<th>FPL</th><td>0.08913<th>GLI</th><td>9.2443<th>GGH</th><td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td></td></td></td>	DZB	3.817763 <th>FPL</th> <td>0.08913<th>GLI</th><td>9.2443<th>GGH</th><td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td></td></td>	FPL	0.08913 <th>GLI</th> <td>9.2443<th>GGH</th><td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td></td>	GLI	9.2443 <th>GGH</th> <td>5.973977<th>IGM</th><td>6.684961<th>INV</th><td>nan</td></td></td>	GGH	5.973977 <th>IGM</th> <td>6.684961<th>INV</th><td>nan</td></td>	IGM	6.684961 <th>INV</th> <td>nan</td>	INV	nan
ACI	nan	AVC	15.87869 <th>DDE</th> <td>10.54667<th>DZG</th><td>nan<th>FVL</th><td>nan<th>GGI</th><td>nan<th>GGN</th><td>5.946637<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td></td></td>	DDE	10.54667 <th>DZG</th> <td>nan<th>FVL</th><td>nan<th>GGI</th><td>nan<th>GGN</th><td>5.946637<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td></td>	DZG	nan <th>FVL</th> <td>nan<th>GGI</th><td>nan<th>GGN</th><td>5.946637<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td>	FVL	nan <th>GGI</th> <td>nan<th>GGN</th><td>5.946637<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td>	GGI	nan <th>GGN</th> <td>5.946637<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td>	GGN	5.946637 <th>IGM</th> <td>nan<th>INW</th><td>nan</td></td>	IGM	nan <th>INW</th> <td>nan</td>	INW	nan
ACJ	nan	AVT	1.71504 <th>DGP</th> <td>4.722865<th>DDM</th><td>8.668958<th>FVS</th><td>8.084528<th>GGI</th><td>nan<th>GGN</th><td>5.407061<th>IGM</th><td>6.584558<th>INW</th><td>5.121818</td></td></td></td></td></td></td>	DGP	4.722865 <th>DDM</th> <td>8.668958<th>FVS</th><td>8.084528<th>GGI</th><td>nan<th>GGN</th><td>5.407061<th>IGM</th><td>6.584558<th>INW</th><td>5.121818</td></td></td></td></td></td>	DDM	8.668958 <th>FVS</th> <td>8.084528<th>GGI</th><td>nan<th>GGN</th><td>5.407061<th>IGM</th><td>6.584558<th>INW</th><td>5.121818</td></td></td></td></td>	FVS	8.084528 <th>GGI</th> <td>nan<th>GGN</th><td>5.407061<th>IGM</th><td>6.584558<th>INW</th><td>5.121818</td></td></td></td>	GGI	nan <th>GGN</th> <td>5.407061<th>IGM</th><td>6.584558<th>INW</th><td>5.121818</td></td></td>	GGN	5.407061 <th>IGM</th> <td>6.584558<th>INW</th><td>5.121818</td></td>	IGM	6.584558 <th>INW</th> <td>5.121818</td>	INW	5.121818
ACI	nan	AVZ	7.044752 <th>DGP</th> <td>9.205036<th>DZT</th><td>4.603773<th>FVA</th></td><td>4.512604<th>GGI</th><td>nan<th>GGN</th><td>5.091818<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td></td>	DGP	9.205036 <th>DZT</th> <td>4.603773<th>FVA</th></td> <td>4.512604<th>GGI</th><td>nan<th>GGN</th><td>5.091818<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td>	DZT	4.603773 <th>FVA</th>	FVA	4.512604 <th>GGI</th> <td>nan<th>GGN</th><td>5.091818<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td>	GGI	nan <th>GGN</th> <td>5.091818<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td>	GGN	5.091818 <th>IGM</th> <td>nan<th>INW</th><td>nan</td></td>	IGM	nan <th>INW</th> <td>nan</td>	INW	nan
ACA	nan	AYA	17.0001 <th>DOS</th> <td>6.283873<th>DZU</th></td> <td>3.22369<th>FVB</th></td> <td>4.128408<th>GGV</th><td>nan<th>GGI</th><td>5.021084<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td></td>	DOS	6.283873 <th>DZU</th>	DZU	3.22369 <th>FVB</th>	FVB	4.128408 <th>GGV</th> <td>nan<th>GGI</th><td>5.021084<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td></td>	GGV	nan <th>GGI</th> <td>5.021084<th>IGM</th><td>nan<th>INW</th><td>nan</td></td></td>	GGI	5.021084 <th>IGM</th> <td>nan<th>INW</th><td>nan</td></td>	IGM	nan <th>INW</th> <td>nan</td>	INW	nan
ACS	nan	AYB	4.178124 <th>DPC</th> <td>nan<th>DCA</th></td> <td>6.060617<th>FVD</th></td> <td>3.186408<th>GGI</th><td>nan<th>GGN</th><td>4.080306<th>HAG</th></td><td>4.899777<th>INW</th><td>7.606318</td></td></td></td>	DPC	nan <th>DCA</th>	DCA	6.060617 <th>FVD</th>	FVD	3.186408 <th>GGI</th> <td>nan<th>GGN</th><td>4.080306<th>HAG</th></td><td>4.899777<th>INW</th><td>7.606318</td></td></td>	GGI	nan <th>GGN</th> <td>4.080306<th>HAG</th></td> <td>4.899777<th>INW</th><td>7.606318</td></td>	GGN	4.080306 <th>HAG</th>	HAG	4.899777 <th>INW</th> <td>7.606318</td>	INW	7.606318
ACC	4.313456355 <th>AZF</th> <td>3.427403<th>DPI</th><td>nan<th>DCA</th></td><td>3.645988<th>FVJ</th><td>3.075541<th>GGI</th><td>nan<th>GGN</th><td>nan<th>HAF</th><td>3.873033<th>INW</th><td>nan</td></td></td></td></td></td></td>	AZF	3.427403 <th>DPI</th> <td>nan<th>DCA</th></td> <td>3.645988<th>FVJ</th><td>3.075541<th>GGI</th><td>nan<th>GGN</th><td>nan<th>HAF</th><td>3.873033<th>INW</th><td>nan</td></td></td></td></td></td>	DPI	nan <th>DCA</th>	DCA	3.645988 <th>FVJ</th> <td>3.075541<th>GGI</th><td>nan<th>GGN</th><td>nan<th>HAF</th><td>3.873033<th>INW</th><td>nan</td></td></td></td></td>	FVJ	3.075541 <th>GGI</th> <td>nan<th>GGN</th><td>nan<th>HAF</th><td>3.873033<th>INW</th><td>nan</td></td></td></td>	GGI	nan <th>GGN</th> <td>nan<th>HAF</th><td>3.873033<th>INW</th><td>nan</td></td></td>	GGN	nan <th>HAF</th> <td>3.873033<th>INW</th><td>nan</td></td>	HAF	3.873033 <th>INW</th> <td>nan</td>	INW	nan
ACD	3.728284392 <th>AJ</th> <td>4.718468<th>DPI</th><td>nan<th>DCA</th></td><td>3.609163<th>FVB</th></td><td>4.107504<th>GGI</th><td>4.433926<th>GGJ</th><td>13.95235<th>IGM</th><td>nan<th>INW</th><td>3.655775</td></td></td></td></td></td>	AJ	4.718468 <th>DPI</th> <td>nan<th>DCA</th></td> <td>3.609163<th>FVB</th></td> <td>4.107504<th>GGI</th><td>4.433926<th>GGJ</th><td>13.95235<th>IGM</th><td>nan<th>INW</th><td>3.655775</td></td></td></td></td>	DPI	nan <th>DCA</th>	DCA	3.609163 <th>FVB</th>	FVB	4.107504 <th>GGI</th> <td>4.433926<th>GGJ</th><td>13.95235<th>IGM</th><td>nan<th>INW</th><td>3.655775</td></td></td></td>	GGI	4.433926 <th>GGJ</th> <td>13.95235<th>IGM</th><td>nan<th>INW</th><td>3.655775</td></td></td>	GGJ	13.95235 <th>IGM</th> <td>nan<th>INW</th><td>3.655775</td></td>	IGM	nan <th>INW</th> <td>3.655775</td>	INW	3.655775
ACK	4.46724472 <th>AZV</th> <td>8.886328<th>DGH</th><td>17.10807<th>DCT</th><td>3.057127<th>FVH</th><td>3.055511<th>GGI</th></td><td>5.343126<th>GGJ</th><td>5.500042<th>IGM</th><td>3.790433<th>INW</th><td>3.738143</td></td></td></td></td></td></td>	AZV	8.886328 <th>DGH</th> <td>17.10807<th>DCT</th><td>3.057127<th>FVH</th><td>3.055511<th>GGI</th></td><td>5.343126<th>GGJ</th><td>5.500042<th>IGM</th><td>3.790433<th>INW</th><td>3.738143</td></td></td></td></td></td>	DGH	17.10807 <th>DCT</th> <td>3.057127<th>FVH</th><td>3.055511<th>GGI</th></td><td>5.343126<th>GGJ</th><td>5.500042<th>IGM</th><td>3.790433<th>INW</th><td>3.738143</td></td></td></td></td>	DCT	3.057127 <th>FVH</th> <td>3.055511<th>GGI</th></td> <td>5.343126<th>GGJ</th><td>5.500042<th>IGM</th><td>3.790433<th>INW</th><td>3.738143</td></td></td></td>	FVH	3.055511 <th>GGI</th>	GGI	5.343126 <th>GGJ</th> <td>5.500042<th>IGM</th><td>3.790433<th>INW</th><td>3.738143</td></td></td>	GGJ	5.500042 <th>IGM</th> <td>3.790433<th>INW</th><td>3.738143</td></td>	IGM	3.790433 <th>INW</th> <td>3.738143</td>	INW	3.738143
ACM	5.528628494 <th>AZZ</th> <td>nan<th>DHI</th><td>nan<th>DCV</th><td>1.77258<th>FVI</th><td>1.289988<th>GGI</th><td>4.31172<th>GGJ</th><td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td></td></td></td></td></td>	AZZ	nan <th>DHI</th> <td>nan<th>DCV</th><td>1.77258<th>FVI</th><td>1.289988<th>GGI</th><td>4.31172<th>GGJ</th><td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td></td></td></td></td>	DHI	nan <th>DCV</th> <td>1.77258<th>FVI</th><td>1.289988<th>GGI</th><td>4.31172<th>GGJ</th><td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td></td></td></td>	DCV	1.77258 <th>FVI</th> <td>1.289988<th>GGI</th><td>4.31172<th>GGJ</th><td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td></td></td>	FVI	1.289988 <th>GGI</th> <td>4.31172<th>GGJ</th><td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td></td>	GGI	4.31172 <th>GGJ</th> <td>nan<th>HGV</th><td>nan<th>INW</th><td>5.832701</td></td></td>	GGJ	nan <th>HGV</th> <td>nan<th>INW</th><td>5.832701</td></td>	HGV	nan <th>INW</th> <td>5.832701</td>	INW	5.832701
ACU	3.567754668 <th>BDC</th> <td>nan<th>DHM</th><td>nan<th>DIB</th><td>0.432751<th>FVI</th><td>nan<th>GGI</th></td><td>6.189077<th>GGJ</th><td>14.54874<th>HIV</th><td>7.745558<th>INW</th><td>7.731704</td></td></td></td></td></td></td>	BDC	nan <th>DHM</th> <td>nan<th>DIB</th><td>0.432751<th>FVI</th><td>nan<th>GGI</th></td><td>6.189077<th>GGJ</th><td>14.54874<th>HIV</th><td>7.745558<th>INW</th><td>7.731704</td></td></td></td></td></td>	DHM	nan <th>DIB</th> <td>0.432751<th>FVI</th><td>nan<th>GGI</th></td><td>6.189077<th>GGJ</th><td>14.54874<th>HIV</th><td>7.745558<th>INW</th><td>7.731704</td></td></td></td></td>	DIB	0.432751 <th>FVI</th> <td>nan<th>GGI</th></td> <td>6.189077<th>GGJ</th><td>14.54874<th>HIV</th><td>7.745558<th>INW</th><td>7.731704</td></td></td></td>	FVI	nan <th>GGI</th>	GGI	6.189077 <th>GGJ</th> <td>14.54874<th>HIV</th><td>7.745558<th>INW</th><td>7.731704</td></td></td>	GGJ	14.54874 <th>HIV</th> <td>7.745558<th>INW</th><td>7.731704</td></td>	HIV	7.745558 <th>INW</th> <td>7.731704</td>	INW	7.731704
ACE	2.356054367 <th>BGP</th> <td>3.329333<th>DHS</th><td>nan<th>DIC</th><td>3.670743<th>FVM</th><td>4.174233<th>GGI</th><td>nan<th>GGV</th><td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td></td></td></td></td></td>	BGP	3.329333 <th>DHS</th> <td>nan<th>DIC</th><td>3.670743<th>FVM</th><td>4.174233<th>GGI</th><td>nan<th>GGV</th><td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td></td></td></td></td>	DHS	nan <th>DIC</th> <td>3.670743<th>FVM</th><td>4.174233<th>GGI</th><td>nan<th>GGV</th><td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td></td></td></td>	DIC	3.670743 <th>FVM</th> <td>4.174233<th>GGI</th><td>nan<th>GGV</th><td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td></td></td>	FVM	4.174233 <th>GGI</th> <td>nan<th>GGV</th><td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td></td>	GGI	nan <th>GGV</th> <td>nan<th>HDI</th><td>8.462034<th>INW</th><td>nan</td></td></td>	GGV	nan <th>HDI</th> <td>8.462034<th>INW</th><td>nan</td></td>	HDI	8.462034 <th>INW</th> <td>nan</td>	INW	nan
ADN	2.462756167 <th>BID</th>	BID	9.34283 <th>DID</th> <td>5.143123<th>DID</th><td>6.66871<th>FVI</th><td>1.881188<th>GGP</th><td>7.84138<th>GGJ</th><td>7.7998<th>HDI</th><td>nan<th>HAC</th><td>nan</td></td></td></td></td></td></td>	DID	5.143123 <th>DID</th> <td>6.66871<th>FVI</th><td>1.881188<th>GGP</th><td>7.84138<th>GGJ</th><td>7.7998<th>HDI</th><td>nan<th>HAC</th><td>nan</td></td></td></td></td></td>	DID	6.66871 <th>FVI</th> <td>1.881188<th>GGP</th><td>7.84138<th>GGJ</th><td>7.7998<th>HDI</th><td>nan<th>HAC</th><td>nan</td></td></td></td></td>	FVI	1.881188 <th>GGP</th> <td>7.84138<th>GGJ</th><td>7.7998<th>HDI</th><td>nan<th>HAC</th><td>nan</td></td></td></td>	GGP	7.84138 <th>GGJ</th> <td>7.7998<th>HDI</th><td>nan<th>HAC</th><td>nan</td></td></td>	GGJ	7.7998 <th>HDI</th> <td>nan<th>HAC</th><td>nan</td></td>	HDI	nan <th>HAC</th> <td>nan</td>	HAC	nan
ADP	4.879287351 <th>BID</th>	BID	nan <th>DIO</th>	DIO	nan <th>DIL</th> <td>3.347128<th>FVT</th><td>3.852277<th>GGI</th></td><td>6.283225<th>DSE</th><td>3.654052<th>HDF</th><td>3.927706<th>MAF</th><td>5.080218</td></td></td></td></td>	DIL	3.347128 <th>FVT</th> <td>3.852277<th>GGI</th></td> <td>6.283225<th>DSE</th><td>3.654052<th>HDF</th><td>3.927706<th>MAF</th><td>5.080218</td></td></td></td>	FVT	3.852277 <th>GGI</th>	GGI	6.283225 <th>DSE</th> <td>3.654052<th>HDF</th><td>3.927706<th>MAF</th><td>5.080218</td></td></td>	DSE	3.654052 <th>HDF</th> <td>3.927706<th>MAF</th><td>5.080218</td></td>	HDF	3.927706 <th>MAF</th> <td>5.080218</td>	MAF	5.080218
ADQ	17.10807360 <th>BIS</th> <td>nan<th>DIE</th><td>nan<th>DIV</th><td>nan<th>FVU</th><td>nan<th>GGV</th><td>0.9793<th>HDE</th><td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td></td></td></td></td></td>	BIS	nan <th>DIE</th> <td>nan<th>DIV</th><td>nan<th>FVU</th><td>nan<th>GGV</th><td>0.9793<th>HDE</th><td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td></td></td></td></td>	DIE	nan <th>DIV</th> <td>nan<th>FVU</th><td>nan<th>GGV</th><td>0.9793<th>HDE</th><td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td></td></td></td>	DIV	nan <th>FVU</th> <td>nan<th>GGV</th><td>0.9793<th>HDE</th><td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td></td></td>	FVU	nan <th>GGV</th> <td>0.9793<th>HDE</th><td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td></td>	GGV	0.9793 <th>HDE</th> <td>4.707138<th>HIF</th><td>5.256164<th>MAF</th><td>nan</td></td></td>	HDE	4.707138 <th>HIF</th> <td>5.256164<th>MAF</th><td>nan</td></td>	HIF	5.256164 <th>MAF</th> <td>nan</td>	MAF	nan
ADJ	2.27031735 <th>BIV</th> <td>nan<th>DID</th><td>nan<th>DIO</th><td>nan<th>FVZ</th><td>nan<th>GGZ</th></td><td>2.46803<th>HDE</th></td><td>5.955008<th>HIV</th><td>nan<th>MAF</th><td>3.251042</td></td></td></td></td></td>	BIV	nan <th>DID</th> <td>nan<th>DIO</th><td>nan<th>FVZ</th><td>nan<th>GGZ</th></td><td>2.46803<th>HDE</th></td><td>5.955008<th>HIV</th><td>nan<th>MAF</th><td>3.251042</td></td></td></td></td>	DID	nan <th>DIO</th> <td>nan<th>FVZ</th><td>nan<th>GGZ</th></td><td>2.46803<th>HDE</th></td><td>5.955008<th>HIV</th><td>nan<th>MAF</th><td>3.251042</td></td></td></td>	DIO	nan <th>FVZ</th> <td>nan<th>GGZ</th></td> <td>2.46803<th>HDE</th></td> <td>5.955008<th>HIV</th><td>nan<th>MAF</th><td>3.251042</td></td></td>	FVZ	nan <th>GGZ</th>	GGZ	2.46803 <th>HDE</th>	HDE	5.955008 <th>HIV</th> <td>nan<th>MAF</th><td>3.251042</td></td>	HIV	nan <th>MAF</th> <td>3.251042</td>	MAF	3.251042
ADK	6.762090156 <th>BVC</th> <td>nan<th>DIB</th><td>nan<th>DIL</th><td>5.048862<th>FVJ</th><td>nan<th>GGZ</th></td><td>5.848788<th>HND</th></td><td>5.112599<th>HIV</th><td>nan<th>MAF</th><td>5.872791</td></td></td></td></td></td>	BVC	nan <th>DIB</th> <td>nan<th>DIL</th><td>5.048862<th>FVJ</th><td>nan<th>GGZ</th></td><td>5.848788<th>HND</th></td><td>5.112599<th>HIV</th><td>nan<th>MAF</th><td>5.872791</td></td></td></td></td>	DIB	nan <th>DIL</th> <td>5.048862<th>FVJ</th><td>nan<th>GGZ</th></td><td>5.848788<th>HND</th></td><td>5.112599<th>HIV</th><td>nan<th>MAF</th><td>5.872791</td></td></td></td>	DIL	5.048862 <th>FVJ</th> <td>nan<th>GGZ</th></td> <td>5.848788<th>HND</th></td> <td>5.112599<th>HIV</th><td>nan<th>MAF</th><td>5.872791</td></td></td>	FVJ	nan <th>GGZ</th>	GGZ	5.848788 <th>HND</th>	HND	5.112599 <th>HIV</th> <td>nan<th>MAF</th><td>5.872791</td></td>	HIV	nan <th>MAF</th> <td>5.872791</td>	MAF	5.872791
AFO	6.6047021 <th>BVM</th> <td>nan<th>DIV</th><td>2.397892<th>DIO</th></td><td>3.151152<th>FZP</th></td><td>8.146593<th>GIA</th><td>nan<th>HIV</th><td>5.853131<th>HGH</th><td>nan<th>MAF</th><td>5.080206</td></td></td></td></td></td>	BVM	nan <th>DIV</th> <td>2.397892<th>DIO</th></td> <td>3.151152<th>FZP</th></td> <td>8.146593<th>GIA</th><td>nan<th>HIV</th><td>5.853131<th>HGH</th><td>nan<th>MAF</th><td>5.080206</td></td></td></td></td>	DIV	2.397892 <th>DIO</th>	DIO	3.151152 <th>FZP</th>	FZP	8.146593 <th>GIA</th> <td>nan<th>HIV</th><td>5.853131<th>HGH</th><td>nan<th>MAF</th><td>5.080206</td></td></td></td>	GIA	nan <th>HIV</th> <td>5.853131<th>HGH</th><td>nan<th>MAF</th><td>5.080206</td></td></td>	HIV	5.853131 <th>HGH</th> <td>nan<th>MAF</th><td>5.080206</td></td>	HGH	nan <th>MAF</th> <td>5.080206</td>	MAF	5.080206
ADP	8.351381816 <th>BVT</th> <td>nan<th>DMG</th></td> <td>nan<th>DIE</th><td>7.675784<th>GAJ</th></td><td>12.72884<th>GIB</th><td>7.608837<th>HSS</th><td>nan<th>HGT</th><td>nan<th>MAF</th><td>11.87105</td></td></td></td></td></td>	BVT	nan <th>DMG</th>	DMG	nan <th>DIE</th> <td>7.675784<th>GAJ</th></td> <td>12.72884<th>GIB</th><td>7.608837<th>HSS</th><td>nan<th>HGT</th><td>nan<th>MAF</th><td>11.87105</td></td></td></td></td>	DIE	7.675784 <th>GAJ</th>	GAJ	12.72884 <th>GIB</th> <td>7.608837<th>HSS</th><td>nan<th>HGT</th><td>nan<th>MAF</th><td>11.87105</td></td></td></td>	GIB	7.608837 <th>HSS</th> <td>nan<th>HGT</th><td>nan<th>MAF</th><td>11.87105</td></td></td>	HSS	nan <th>HGT</th> <td>nan<th>MAF</th><td>11.87105</td></td>	HGT	nan <th>MAF</th> <td>11.87105</td>	MAF	11.87105
ADJ	7.021435504 <th>BVJ</th> <td>nan<th>DNL</th><td>nan<th>DIN</th><td>8.280205<th>GAC</th></td><td>nan<th>GID</th><td>nan<th>GTA</th></td><td>5.880769<th>HGV</th><td>nan<th>MAF</th><td>8.430142</td></td></td></td></td></td>	BVJ	nan <th>DNL</th> <td>nan<th>DIN</th><td>8.280205<th>GAC</th></td><td>nan<th>GID</th><td>nan<th>GTA</th></td><td>5.880769<th>HGV</th><td>nan<th>MAF</th><td>8.430142</td></td></td></td></td>	DNL	nan <th>DIN</th> <td>8.280205<th>GAC</th></td> <td>nan<th>GID</th><td>nan<th>GTA</th></td><td>5.880769<th>HGV</th><td>nan<th>MAF</th><td>8.430142</td></td></td></td>	DIN	8.280205 <th>GAC</th>	GAC	nan <th>GID</th> <td>nan<th>GTA</th></td> <td>5.880769<th>HGV</th><td>nan<th>MAF</th><td>8.430142</td></td></td>	GID	nan <th>GTA</th>	GTA	5.880769 <th>HGV</th> <td>nan<th>MAF</th><td>8.430142</td></td>	HGV	nan <th>MAF</th> <td>8.430142</td>	MAF	8.430142
ADV	6.006247825 <th>CEY</th>	CEY	12.35981 <th>DMO</th>	DMO	8.756878 <th>DIV</th>	DIV	3.205832 <th>GAJ</th>	GAJ	5.783716 <th>GIE</th>	GIE	9.258482 <th>HIV</th>	HIV	3.204899 <th>HIV</th> <td>6.930848<th>MAF</th><td>10.31749</td></td>	HIV	6.930848 <th>MAF</th> <td>10.31749</td>	MAF	10.31749
ADG	7.390013319 <th>CID</th>	CID	8.826256 <th>DAN</th>	DAN	nan <th>DIO</th> <td>2.880807<th>GAF</th></td> <td>4.22155<th>GIL</th></td> <td>9.258482<th>GTK</th></td> <td>7.910083<th>HIA</th></td> <td>6.925887<th>MAF</th><td>8.024061</td></td>	DIO	2.880807 <th>GAF</th>	GAF	4.22155 <th>GIL</th>	GIL	9.258482 <th>GTK</th>	GTK	7.910083 <th>HIA</th>	HIA	6.925887 <th>MAF</th> <td>8.024061</td>	MAF	8.024061
ADH	4.068278344 <th>CIF</th> <td>nan<th>DOD</th><td>nan<th>DCV</th></td><td>1.446343<th>GAG</th></td><td>7.880548<th>GIM</th><td>nan<th>GTL</th></td><td>2.544005<th>HIS</th></td><td>nan<th>MAF</th><td>nan</td></td></td></td>	CIF	nan <th>DOD</th> <td>nan<th>DCV</th></td> <td>1.446343<th>GAG</th></td> <td>7.880548<th>GIM</th><td>nan<th>GTL</th></td><td>2.544005<th>HIS</th></td><td>nan<th>MAF</th><td>nan</td></td></td>	DOD	nan <th>DCV</th>	DCV	1.446343 <th>GAG</th>	GAG	7.880548 <th>GIM</th> <td>nan<th>GTL</th></td> <td>2.544005<th>HIS</th></td> <td>nan<th>MAF</th><td>nan</td></td>	GIM	nan <th>GTL</th>	GTL	2.544005 <th>HIS</th>	HIS	nan <th>MAF</th> <td>nan</td>	MAF	nan
ADH	7.808553762 <th>CIG</th>	CIG	9.412866 <th>DOK</th> <td>nan<th>DOD</th></td> <td>14.25883<th>GAH</th></td> <td>15.42518<th>GIM</th></td> <td>5.159902<th>GTM</th><td>nan<th>HIS</th></td><td>nan<th>MAF</th><td>12.68818</td></td></td>	DOK	nan <th>DOD</th>	DOD	14.25883 <th>GAH</th>	GAH	15.42518 <th>GIM</th>	GIM	5.159902 <th>GTM</th> <td>nan<th>HIS</th></td> <td>nan<th>MAF</th><td>12.68818</td></td>	GTM	nan <th>HIS</th>	HIS	nan <th>MAF</th> <td>12.68818</td>	MAF	12.68818
ADH	4.385667404 <th>CIN</th> <td>nan<th>DOK</th><td>nan<th>DOD</th></td><td>nan<th>GAJ</th></td><td>nan<th>GIM</th></td><td>9.722738<th>GTY</th></td><td>5.204323<th>HIS</th></td><td>5.097751<th>MAF</th><td>nan</td></td></td>	CIN	nan <th>DOK</th> <td>nan<th>DOD</th></td> <td>nan<th>GAJ</th></td> <td>nan<th>GIM</th></td> <td>9.722738<th>GTY</th></td> <td>5.204323<th>HIS</th></td> <td>5.097751<th>MAF</th><td>nan</td></td>	DOK	nan <th>DOD</th>	DOD	nan <th>GAJ</th>	GAJ	nan <th>GIM</th>	GIM	9.722738 <th>GTY</th>	GTY	5.204323 <th>HIS</th>	HIS	5.097751 <th>MAF</th> <td>nan</td>	MAF	nan
ADH	8.071819351 <th>CTP</th>	CTP	8.339939 <th>DON</th>	DON	8.433933 <th>DIV</th>	DIV	nan <th>GAJ</th>	GAJ	4.920879 <th>GIV</th>	GIV	nan <th>GUA</th>	GUA	4.184863 <th>HIS</th>	HIS	5.401083 <th>MAF</th>	MAF	1.531261
ADH	6.278895043 <th>CTG</th>	CTG	4.118208 <th>DPI</th>	DPI	nan <th>DIO</th>	DIO	3.032774 <th>GAL</th>	GAL	2.600288 <th>GIV</th>	GIV	12.43186 <th>GUA</th>	GUA	6.65876 <th>HIS</th>	HIS	nan <th>MAF</th>	MAF	8.848161
ADH	5.980526735 <th>CTM</th>	CTM	6.056703 <th>DPI</th>	DPI	11.0092 <th>DPI</th>	DPI	10.57339 <th>GAM</th>	GAM	3.757137 <th>GBH</th>	GBH	nan <th>GUA</th>	GUA	5.841109 <th>HMC</th>	HMC	nan <th>MAF</th>	MAF	8.040841
ADH	3.346371418 <th>CTP</th>	CTP	8.693054 <th>DPC</th>	DPC	8.839371 <th>DPI</th>	DPI	0.004476 <th>GAJ</th>	GAJ	7.697759 <th>GBC</th>	GBC	8.84343 <th>GUA</th>	GUA	2.36111 <th>HMS</th>	HMS	3.816248 <th>ICD</th>	ICD	12.74032
ADH	8.830370383 <th>CTV</th>	CTV	7.13808 <th>DPE</th>	DPE	9.839415 <th>DPI</th>	DPI	7.49582 <th>GAJ</th>	GAJ	5.073993 <th>GBC</th>	GBC	6.22188 <th>GUM</th>	GUM	3.758526 <th>HMS</th>	HMS	2.842831 <th>ICD</th>	ICD	3.312031
ADH	8.821579367 <th>CVA</th>	CVA	nan <th>DPI</th>	DPI	15.12202 <th>FFB</th>	FFB	8.867887 <th>SAV</th> <td>nan<th>GBC</th></td> <td>6.199789<th>GUA</th></td> <td>nan<th>ICD</th></td> <td>nan<th>MAF</th></td> <td>8.082087</td>	SAV	nan <th>GBC</th>	GBC	6.199789 <th>GUA</th>	GUA	nan <th>ICD</th>	ICD	nan <th>MAF</th>	MAF	8.082087
ADH	5.602080597 <th>CVB</th> <td>nan<th>DPI</th></td> <td>2.567724<th>FVJ</th></td> <td>9.012803<th>GBC</th></td> <td>3.882823<th>GBV</th><td>nan<th>CVB</th><td>nan<th>HMS</th></td><td>nan<th>MAF</th></td><td>8.530537</td></td></td>	CVB	nan <th>DPI</th>	DPI	2.567724 <th>FVJ</th>	FVJ	9.012803 <th>GBC</th>	GBC	3.882823 <th>GBV</th> <td>nan<th>CVB</th><td>nan<th>HMS</th></td><td>nan<th>MAF</th></td><td>8.530537</td></td>	GBV	nan <th>CVB</th> <td>nan<th>HMS</th></td> <td>nan<th>MAF</th></td> <td>8.530537</td>	CVB	nan <th>HMS</th>	HMS	nan <th>MAF</th>	MAF	8.530537
ADH	0.377249948 <th>CVC</th>	CVC	nan <th>DPI</th>	DPI	4.585354 <th>FIR</th>	FIR	3.780163 <th>GBC</th>	GBC	4.348483 <th>GBC</th>	GBC	4.307886 <th>GCN</th> <td>nan<th>MMI</th></td> <td>6.357372<th>ICD</th><td>nan</td></td>	GCN	nan <th>MMI</th>	MMI	6.357372 <th>ICD</th> <td>nan</td>	ICD	nan
ADH	11.780186872 <th>CVD</th> <td>nan<th>DPI</th></td> <td>6.776397<th>FIB</th></td> <td>5.722183<th>GBC</th></td> <td>4.007141<th>GLI</th></td> <td>nan<th>GVD</th><td>nan<th>MMV</th><td>nan<th>ICJ</th><td>7.26842</td></td></td></td>	CVD	nan <th>DPI</th>	DPI	6.776397 <th>FIB</th>	FIB	5.722183 <th>GBC</th>	GBC	4.007141 <th>GLI</th>	GLI	nan <th>GVD</th> <td>nan<th>MMV</th><td>nan<th>ICJ</th><td>7.26842</td></td></td>	GVD	nan <th>MMV</th> <td>nan<th>ICJ</th><td>7.26842</td></td>	MMV	nan <th>ICJ</th> <td>7.26842</td>	ICJ	7.26842
ADH	8.808547434 <th>CVE</th>	CVE	nan <th>DPI</th>	DPI	9.908902 <th>DIC</th>	DIC	9.385125 <th>GBN</th>	GBN	1.385924 <th>GIM</th>	GIM	nan <th>GVN</th> <td>nan<th>HMI</th></td> <td>5.080955<th>ICU</th><td>nan</td></td>	GVN	nan <th>HMI</th>	HMI	5.080955 <th>ICU</th> <td>nan</td>	ICU	nan
ADH	8.18257167 <th>CVT</th>	CVT	nan <th>DPI</th>	DPI	6.692378 <th>FLI</th>	FLI	3.00437 <th>GBP</th> <td>nan<th>GLM</th></td> <td>nan<th>GVI</th><td>nan<th>HCA</th></td><td>6.668186<th>ICV</th><td>3.878109</td></td></td>	GBP	nan <th>GLM</th>	GLM	nan <th>GVI</th> <td>nan<th>HCA</th></td> <td>6.668186<th>ICV</th><td>3.878109</td></td>	GVI	nan <th>HCA</th>	HCA	6.668186 <th>ICV</th> <td>3.878109</td>	ICV	3.878109
ADH	7.739888461 <th>DAC</th>	DAC	nan <th>DPI</th>	DPI	4.341424 <th>ITF</th>	ITF	0.016464 <th>GBY</th> <td>nan<th>GLN</th></td> <td>nan<th>GVL</th><td>nan<th>HCV</th><td>7.738083<th>ICZ</th><td>8.880243</td></td></td></td>	GBY	nan <th>GLN</th>	GLN	nan <th>GVL</th> <td>nan<th>HCV</th><td>7.738083<th>ICZ</th><td>8.880243</td></td></td>	GVL	nan <th>HCV</th> <td>7.738083<th>ICZ</th><td>8.880243</td></td>	HCV	7.738083 <th>ICZ</th> <td>8.880243</td>	ICZ	8.880243
ADH	4.544606757 <th>DAN</th>	DAN	8.737035 <th>DIZ</th>	DIZ	10.54804 <th>FIB</th>	FIB	5.498019 <th>GBC</th> <td>nan<th>GLP</th></td> <td>5.994002<th>GVZ</th></td> <td>nan<th>HPC</th></td> <td>4.780294<th>ICZ</th><td>4.514004</td></td>	GBC	nan <th>GLP</th>	GLP	5.994002 <th>GVZ</th>	GVZ	nan <th>HPC</th>	HPC	4.780294 <th>ICZ</th> <td>4.514004</td>	ICZ	4.514004
ADH	5.278058253 <th>DAI</th>	DAI	5.747137 <th>DIO</th>	DIO	9.825308 <th>FAC</th>	FAC	5.6113 <th>GCA</th>	GCA	nan <th>GLI</th>	GLI	7.158363 <th>GVZ</th>	GVZ	nan <th>HPI</th>	HPI	11.89438 <th>ICZ</th> <td>7.198886</td>	ICZ	7.198886
ADH	10.29168972 <th>DAL</th>	DAL	nan <th>DIC</th>	DIC	8.666136 <th>FIM</th>	FIM	9.900836 <th>GCC</th>	GCC	nan <th>GLV</th>	GLV	nan <th>GVZ</th>	GVZ	nan <th>HPP</th>	HPP	3.094547 <th>ICZ</th> <td>5.57674</td>	ICZ	5.57674
ADH	3.382885587 <th>DAS</th>	DAS	nan <th>DID</th>	DID	8.873536 <th>FIN</th> <td>nan<th>GCD</th></td> <td>nan<th>GLI</th></td> <td>0.888889<th>GYS</th></td> <td>nan<th>HPI</th></td> <td>4.436253<th>ICL</th></td> <td>2.52088</td>	FIN	nan <th>GCD</th>	GCD	nan <th>GLI</th>	GLI	0.888889 <th>GYS</th>	GYS	nan <th>HPI</th>	HPI	4.436253 <th>ICL</th>	ICL	2.52088
ADH	4.344041806 <th>DAT</th>	DAT	9.688347 <th>DIP</th>	DIP	10.89243 <th>FIZ</th>	FIZ	12.28183 <th>GCB</th> <td>nan<th>GMA</th></td> <td>5.911733<th>GVN</th><td>3.91078<th>HPI</th></td><td>nan<th>ICL</th></td><td>5.094664</td></td>	GCB	nan <th>GMA</th>	GMA	5.911733 <th>GVN</th> <td>3.91078<th>HPI</th></td> <td>nan<th>ICL</th></td> <td>5.094664</td>	GVN	3.91078 <th>HPI</th>	HPI	nan <th>ICL</th>	ICL	5.094664
ADH	3.382885587 <th>DAZ</th>	DAZ	5.018154 <th>DVB</th> <td>nan<th>FMO</th></td> <td>11.00219<th>GCD</th></td> <td>nan<th>GMC</th></td> <td>nan<th>GVL</th></td> <td>5.900714<th>HPL</th></td> <td>nan<th>ICV</th><td>nan</td></td>	DVB	nan <th>FMO</th>	FMO	11.00219 <th>GCD</th>	GCD	nan <th>GMC</th>	GMC	nan <th>GVL</th>	GVL	5.900714 <th>HPL</th>	HPL	nan <th>ICV</th> <td>nan</td>	ICV	nan
ADH	6.682733835 <th>DIA</th>	DIA	5.704006 <th>DIV</th> <td>nan<th>FPI</th></td> <td>9.474058<th>GCI</th></td> <td>nan<th>GMD</th></td> <td>nan<th>GYN</th><td>nan<th>HPC</th></td><td>4.514072<th>ICV</th><td>18.55831</td></td></td>	DIV	nan <th>FPI</th>	FPI	9.474058 <th>GCI</th>	GCI	nan <th>GMD</th>	GMD	nan <th>GYN</th> <td>nan<th>HPC</th></td> <td>4.514072<th>ICV</th><td>18.55831</td></td>	GYN	nan <th>HPC</th>	HPC	4.514072 <th>ICV</th> <td>18.55831</td>	ICV	18.55831
ADH	8.803146138 <th>DIB</th>	DIB	4.399548 <th>DIZ</th>	DIZ	nan <th>FPI</th>	FPI	2.826181 <th>GCI</th>	GCI	nan <th>GMD</th>	GMD	nan <th>GYN</th>	GYN	nan <th>HPC</th>	HPC	4.490824 <th>ICV</th>	ICV	nan
ADH	5.640780939 <th>DIO</th>	DIO	8.581213 <th>DIZ</th>	DIZ	nan <th>FPI</th>	FPI	5.009907 <th>GCI</th>	GCI	nan <th>GMD</th>	GMD	nan <th>GYN</th>	GYN	nan <th>HPC</th>	HPC	4.514071 <th>ICV</th>	ICV	nan
ADH	2.068611101 <th>DIN</th>	DIN	30.28804 <th>DVA</th>	DVA	nan <th>FFB</th>	FFB	3.38354 <th>GDE</th>	GDE	8.974283 <th>GMI</th>	GMI	nan <th>GZV</th>	GZV	7.896708 <th>HPI</th>	HPI	12.74472 <th>ICV</th>	ICV	nan
ADH	9.422335883 <th>DNE</th>	DNE	6.38128 <th>DVC</th> <td>nan<th>FFZ</th></td> <td>9.380083<th>GEC</th><td>nan<th>GMP</th></td><td>9.000734<th>GZL</th></td><td>nan<th>HSA</th></td><td>5.107458<th>ICV</th><td>nan</td></td></td>	DVC	nan <th>FFZ</th>	FFZ	9.380083 <th>GEC</th> <td>nan<th>GMP</th></td> <td>9.000734<th>GZL</th></td> <td>nan<th>HSA</th></td> <td>5.107458<th>ICV</th><td>nan</td></td>	GEC	nan <th>GMP</th>	GMP	9.000734 <th>GZL</th>	GZL	nan <th>HSA</th>	HSA	5.107458 <th>ICV</th> <td>nan</td>	ICV	nan
ADH	8.897788899 <th>DNP</th>	DNP	11.45788 <th>DVI</th>	DVI	nan <th>FBA</th>	FBA	2.327748 <th>GFI</th>	GFI	9.28911 <th>GZV</th>	GZV	5.997398 <th>HIV</th>	HIV	3.997398 <th>HSA</th>	HSA	3.982828 <th>ICV</th> <td>nan</td>	ICV	nan
ADH	5.348916013 <th>DNE</th>	DNE	20.0391 <th>DVN</th> <td>nan<th>FFZ</th></td> <td>3.703446<th>GFA</th></td> <td>nan<th>GMY</th></td> <td>3.44005<th>HST</th></td> <td>11.45553<th>ICV</th></td> <td>5.786447<th>ICV</th></td> <td>nan</td>	DVN	nan <th>FFZ</th>	FFZ	3.703446 <th>GFA</th>	GFA	nan <th>GMY</th>	GMY	3.44005 <th>HST</th>	HST	11.45553 <th>ICV</th>	ICV	5.786447 <th>ICV</th>	ICV	nan
ADH	6.124891654 <th>DOR</th> <td>nan<th>DVO</th></td> <td>nan<th>FBE</th><td>nan<th>GFB</th><td>nan<th>GZV</th></td><td>8.522934<th>HST</th></td><td>9.862367<th>HIZ</th></td><td>nan<th>ICV</th></td><td>nan</td></td></td>	DOR	nan <th>DVO</th>	DVO	nan <th>FBE</th> <td>nan<th>GFB</th><td>nan<th>GZV</th></td><td>8.522934<th>HST</th></td><td>9.862367<th>HIZ</th></td><td>nan<th>ICV</th></td><td>nan</td></td>	FBE	nan <th>GFB</th> <td>nan<th>GZV</th></td> <td>8.522934<th>HST</th></td> <td>9.862367<th>HIZ</th></td> <td>nan<th>ICV</th></td> <td>nan</td>	GFB	nan <th>GZV</th>	GZV	8.522934 <th>HST</th>	HST	9.862367 <th>HIZ</th>	HIZ	nan <th>ICV</th>	ICV	nan

Figure 28. Excess Kurtosis Calculation Between “01.01.2022” to “01.01.2021”

AAI	1.17114843518467117	ABP	6.400296907198129	BCD	5.101170412113880001	DVU	N/A	FIP	4.41553913841542708	EPD	5.17541081171004319	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
AAJ	1.8579351464140255	ABU	8.555058	DCE	5.177777777777778	DVU	N/A	FIR	1.79399113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
AAK	1.1014843518467117	ABM	3.170464	DCP	6.773358	DVZ	N/A	FJA	1.79399113841542708	EPF	5.17541081171004319	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
AAV	1.1014843518467117	ABP	6.665951	DCV	N/A	DVU	N/A	FJA	9.94076413841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ABG	3.271878131	ATI	8.105591	DGA	3.912135	DVN	N/A	FJM	5.101170412113880001	EPD	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACI	N/A	AUT	17.10807	DDC	4.523398	DVU	N/A	FLP	0.0891313841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACJ	N/A	AVC	15.87869	DDE	10.54667	DVG	N/A	FVL	5.177777777777778	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACK	N/A	AVT	1.71504	DGP	4.722865	DVM	8.668958	FVJ	8.08452813841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACL	N/A	AVZ	7.044752	DGP	9.205036	DVT	4.603773	FVA	4.51260413841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACA	N/A	AYA	17.0001	DOS	6.283873	DVO	3.22369	FVB	4.12840813841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACC	4.313456355	AZF	3.427403	DVD	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACD	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACE	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACF	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACG	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACH	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACI	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACJ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACK	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACL	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACM	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACN	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACO	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACP	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACQ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACR	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACS	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACT	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACU	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACV	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACW	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACX	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACY	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ACZ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADA	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADB	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADC	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADD	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADE	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADF	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADG	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADH	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADI	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADJ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADK	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADL	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADM	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADN	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADO	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADP	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADQ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADR	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADS	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADT	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADU	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADV	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADW	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADX	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADY	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
ADZ	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN	N/A	INW	N/A	INZ	N/A
AEA	3.728284392	AJ	4.718468	DVI	N/A	DCA	3.645988	FVJ	3.07554113841542708	EPF	N/A	GGI	N/A	GGN	5.17541081171004319	IGN					

3.7 Ranking Methodology

The methodology applied in this study harnesses the capabilities of Multi-criteria Analysis (MA) or Multiple Criteria Decision Making (MCDM). MCDM, a tool widely deployed in the ranking or selection of options, allows for the evaluation of a set of alternatives against multiple and often conflicting criteria (Yoon & Hwang, 1981). Given the multifaceted characteristics of different funds in the financial market, MA provides a valuable framework for comparative analysis in evaluating a multitude of financial ratios to rank different funds based on their overall performance. This research employs the Entropy Multi Attribute Decision Making approach to assign weights to each financial ratio, creating a comprehensive ranking of funds.

The underlying rationale of this method originates from the concept of order preference by similarity to an ideal solution, also known as the TOPSIS model (Yoon & Hwang, 1981). The model's concept is intuitive and logical, its computations are straightforward, it effectively represents the search for the best performing fund for each financial ratio in a simple mathematical expression, and importantly, allows for the assignment of individual weights in the comparison process. According to this model, the optimal alternative should be as close as possible to the positive ideal solution and as far as possible from the negative ideal solution, so a normalization process is also needed.

Within our ranking system, the funds are denoted as $F=\{F_i, i=1,2,\dots,n\}$ and will be evaluated against the financial ratios that we have, which are represented as $C=\{C_j, j=1,2,\dots,m\}$. The ratings for each fund F_i in relation to each criterion C_j will be a definite value, calculated from the data already obtained from the Python system and corresponding Excel files. To apply the model, a decision matrix is constructed where x_{ij} represents the definitive values indicating the performance rating of each F_i value with respect to each criterion C_j .

$$\text{Decision Matrix } X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}$$

The decision matrix, represented as X, must be normalized to ensure all criteria are benefit criteria, as the model requires each criterion to be monotonic. The normalization process can accomplish this without any loss of the data. The relative importance of the criteria is determined by the subjective preferences reflected in the decision matrix and the objective characteristics of our criteria (Zeleny, 1982). The process of assigning subjective preferences to each criterion is known as subjective weighting (Chung-Hsing, Hepu, & Willis, 2000). In the MA systems, there are several methods to assign subjective weights to criteria and all of them vary in their results in terms of subjective weight assignment. This is because of the fact that the DM systems cannot always give the same results under varying weighting schemes and the process itself is basically context dependent (Barrett & Barron, 1996) (Hobbs, 1978) (Waid & Schoemaker, 1982). For our system the entropy methodology is considered to be the most effective model for calculating weights for financial ratios due to its capability to clearly present the volume of decision information each financial ratio encompasses (Yoon & Hwang, 1981).

Entropy is a concept derived from probability theory that quantifies the level of uncertainty or randomness in information. The higher the entropy, the greater the degree of uncertainty. Specifically, a distribution that is more dispersed embodies a higher degree of uncertainty compared to one that is acutely peaked. In order to ascertain objective weights through the entropy measure, the decision matrix, must undergo a process of normalization for each respective criterion.

To normalize our values first we have to differentiate the criteria as Benefit and Cost criteria and use the formulas accordingly.

$$\text{For Benefit Criteria Normalization} = (x_{ij} - x_{ijmin}) / (x_{ijmax} - x_{ijmin})$$

$$\text{For Cost Criteria Normalization} = (x_{ijmax} - x_{ij}) / (x_{ijmax} - x_{ijmin})$$

After the decision matrix is normalized, we obtain a new matrix containing the normalized benefit values of all our data, represented as matrix P.

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1m} \\ p_{21} & p_{22} & \dots & p_{2m} \\ \dots & \dots & \dots & \dots \\ p_{n1} & p_{n2} & \dots & p_{nm} \end{bmatrix}$$

The entropy value, e_j , measures the quantity of decision information contained in the normalization matrix and emitted from each criterion C_j (j being a variable that can take values from 1 to m).

The entropy value, denoted as e_j , measures the quantity of decision-related information that is encompassed in normalization matrix and emitted from each criterion, C_j (j being a variable that can take values from 1 to m). The mathematical expression for this entropy value, e_j , is given as:

$$e_j = -k * \sum_{i=1}^n p_{ij} * \ln(p_{ij})$$

The constant k equals $1/\ln(n)$, where n represents the number of entries, and this constant ensures that the entropy value, e_j , lies between 0 and 1. In essence, this formula quantifies the degree of uncertainty or randomness associated with each decision criterion, C_j .

The extent of disparity or divergence, symbolized by d_j , of the mean inherent information contained by each criterion, C_j (where j ranges from 1 to m), can be computed as:

$$d_j = 1 - e_j$$

The variable d_j stands for the intrinsic intensity of contrast for the criterion C_j . The greater the divergence in the performance ratings, P_{ij} (where i varies from 1 to n), for the criterion C_j , the higher will be the associated d_j . Consequently, the importance of the criterion C_j for the problem increases with the degree of divergence in the performance ratings (Zeleny, 1982). This implies that a criterion is less significant for a specific issue if all options exhibit similar performance ratings for that criterion (de Korvin, Shipley, & Obid, 1991). If performance ratings are identical for a particular criterion, then that criterion can be disregarded in the given context requiring a decision, because it provides no valuable information to the decision maker (Zeleny, 1982).

Thus, the weights subjective to each criterion can be calculated by;

$$w_j = \frac{d_j}{\sum_{k=1}^m d_k}$$

Upon computation of the weights associated with each criterion, our study proceeded to employ the Simple Additive Weighting (SAW) methodology, a commonly applied Multi Criteria Decision Making (MCDM) technique. The objective was to rank all funds according to their final score, which is calculated by multiplying the values of each criterion by their corresponding weights.

The SAW methodology, known for its simplicity and interpretability, assumes that an option's worth is the sum of its weighted performances (Churchmann & Ackoff, 1954). Each performance value is multiplied by the associated weight, and these products are then summed to calculate the final score for each fund. This technique allows the scores to represent the overall performance of the funds, thus facilitating a comprehensive comparison.

The SAW method can be described by the following formula:

$$Final\ Score = \bar{P}_i = \sum_{j=1}^m P_{ij}w_j$$

In this formula, P_{ij} are the normalized values derived from each criterion, and w_j represents the subjective weights associated with each criterion. This method ensures that the relative importance of each criterion is appropriately reflected in the final ranking of the funds.

This combination of entropy weighting and SAW ranking offers a balanced and nuanced approach to fund evaluation. By considering both the inherent uncertainty (measured via entropy) and the aggregated performance (calculated using SAW), this method presents a comprehensive and robust fund ranking methodology. As such, it provides a valuable tool for investors, fund managers, and financial analysts, facilitating more informed and accurate decision-making in the complex and multifaceted world of financial markets.

Chapter 4

Findings[MYP5][NAG6]

4.1 Ranking Results

Following the methodology described in the previous sections, we commenced by generating financial ratio data for the period spanning from February 1, 2020 to February 2, 2022. This data was generated utilizing the custom-designed Python-based program detailed earlier.

To ensure a comprehensive yearly analysis, we adopted a rolling process for our calculations. This approach began with the first set of results covering the period from January 1, 2021, to February 2, 2022. And subsequently, ended at the set of financial ratio results that spanned from January 1, 2022, to December 1, 2020. This method allowed us to incorporate every month within our two-year window by shifting the calculation back one month at each iteration. This process concluded with our twelfth calculation, covering the period from February 1, 2020, to March 1, 2021, thereby ensuring a complete year-round analysis.

Upon the completion of the financial ratio calculations for each time frame, the next phase entailed assembling decision matrices. These matrices encompassed all the financial ratios and their corresponding funds in a matrix format for each specific time period. Representative examples of decision matrices for various time spans are presented in the figures below.

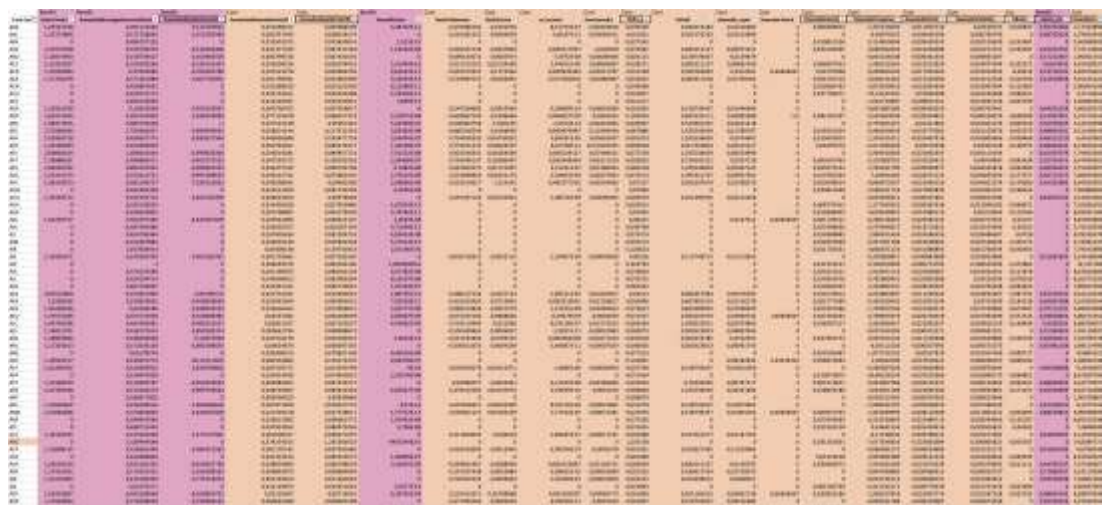
The image shows a highly detailed and dense table, likely a decision matrix, with numerous columns and rows. The table is organized into several distinct sections, with columns labeled with various financial ratios and metrics. The rows represent different time periods or funds. The data is presented in a structured, tabular format, with each cell containing numerical values or text. The table is color-coded, with alternating shades of purple and orange for the columns, and a light blue background for the rows. The overall layout is complex and technical, typical of financial data analysis.

Figure 30. Example from the first Decision Matrix of 01.01.2021-02.02.2022

Figure 31. Example from Ninth Decision Matrix of 01.06.2021-01.05.2020

Figure 32. Example from Final Decision Matrix of 01.03.2021-01.02.2020

This process necessitated the review of all the financial ratios for each month to eliminate any that were ineffective or posed potential computational problems. This was due to an overall scarcity of data, and a significant lack of data for certain periods. Notably, a substantial lack of benchmark price data led to the exclusion of additional financial ratios in some date ranges.

For instance, the twelfth decision matrix was limited to 70 financial ratios, due to the need to exclude ratios such as "Ewma Correlation", "Sortino Ratio", "Spearman Correlation", "Risk Free Mean" and "Risk Free Total". These exclusions were made because of the widespread data deficiencies. Furthermore, both "Risk Free Mean" and "Risk Free Total" had to be discarded as they consistently returned

identical results for all funds in the dataset. Thus, in our 5th decision matrix for example, we had the usage of 64 financial ratios. As was mentioned previously, during the formation of each decision matrix, due to the exclusion of different financial ratios, the total sum of decision criteria varied from date span to date span between 58 to 70 financial ratios.

As the date shifting progressed, each decision matrix necessitated the exclusion of a unique ratio due to inadequate data. This issue was predominantly due to the lack of benchmark data. For example, the fifth decision matrix required the removal of financial ratios like "BetaCoSkewness", "BetaCovariance", and "CoKurtosis", owing to insufficient benchmark data for their computation. Furthermore, in each different matrix different fund were excluded or included into the final selection in regards to the data at hand. Again because of lack of data overall and the lack of benchmark data some funds had to be excluded or included in different time spans. For example the first excel had a total of 734 funds during the January 1, 2021, to February 2, 2022 period, from the initial 1122 funds at hand. Other matrices number of funds used in the calculation varied from 638 to 740. Also, each matrix had a different set of funds according to whether if there was meaningful data during the time spans or not. The decision to exclude these ratios and funds was carefully considered to maintain the robustness and accuracy of our analysis.

Having successfully curated the decision matrices, the next step was to assign weights to the remaining financial ratios using the entropy-based methodology as discussed earlier. The process was executed individually for each decision matrix, thus enabling us to allocate weights that accurately reflect the intrinsic characteristics of the data in each specific period.

The computation of weights, however, wasn't a straightforward task. The inherent nature of entropy methodology entails that it assigns a lower weight to a criterion when the performance ratings of alternatives for that criterion are similar. In certain months, we observed that some financial ratios resulted in similar performance ratings across various funds, which in turn resulted in those ratios being assigned lower weights. This observation was consistently noted across different periods of time, thereby making it a crucial factor that influenced the fund rankings significantly. To avoid this calculation error, we also excluded financial ratios that has similar performance ratings.

Following the determination of weights, we employed the Simple Additive Weighting (SAW) technique to rank the funds. Each fund's score was calculated as the weighted sum of its performance ratings across all the criteria, with weights determined by the entropy measure. This technique allowed us to generate a comprehensive and easily interpretable ranking for the funds, while simultaneously taking into account the multi-faceted nature of the performance criteria.

The dynamic nature of this ranking system was attributed to the monthly shifting of the calculation period, thereby allowing it to adapt to fund performance variations over time. Rankings were derived for each month within the two-year frame, reflecting changes in fund performance and the varying weights allocated to the financial ratios. However, these rankings were affected by challenges such as the varying number of financial ratios in each decision matrix and the normalization process, which involved the transformation of each financial ratio and reassessment of the benefit/cost nature of the criteria for each decision matrix.

Despite these challenges, the application of the entropy methodology and the SAW technique resulted in a robust ranking system that accurately captured the performance of the funds. This detailed examination of fund performance over the two-year period yielded insights beneficial to stakeholders in the financial market.

The normalization process played a pivotal role in adjusting all performance ratings in the decision matrix to a comparable scale. The objective of normalization is to ensure that the different metrics, which may initially be measured on different scales, can be compared fairly. This is especially crucial in our context, where the various financial ratios have different units and ranges of values.

In our analysis, we performed normalization separately for the benefit and cost criteria. The normalization formula for benefit criteria is given by:

$$\text{For Benefit Criteria Normalization} = (x_{ij} - x_{ijmin}) / (x_{ijmax} - x_{ijmin})$$

While for cost criteria, the formula is:

$$\text{For Cost Criteria Normalization} = (x_{ijmax} - x_{ij}) / (x_{ijmax} - x_{ijmin})$$

Here, x_{ij} represents the initial performance rating of fund i on criterion j , while x_{ijmin} and x_{ijmax} represent the minimum and maximum performance ratings of all funds on criterion j , respectively.

By transforming the performance ratings in this way, all criteria are converted into benefit criteria, and all performance ratings fall within the range of 0 to 1, making them directly comparable. Importantly, this transformation retains the relative performance of the funds on each criterion.

In the context of our normalization process, encountering zero values presented a specific challenge because the entropy weight calculation, as derived from probability theory, does not accommodate such values. Zero values would lead to undefined terms in the entropy calculation due to the presence of logarithmic functions.

To manage this situation, we implemented a strategy of assigning dummy values to replace these zero values in the normalized data matrix. The specific dummy value chosen to replace the zero values in our normalization matrix was 1E-16. This is an extremely small positive number, almost infinitesimally close to zero, which makes it an excellent choice to minimally disturb the overall distribution of the normalized data.

The selection of 1E-16 ensured that the entropy calculations could proceed smoothly without running into computational issues associated with zero values, while preserving the relative performance ratings of the funds in the normalization matrix. This careful choice played a critical role in the successful implementation of our entropy-based weight calculation, contributing to the reliability and accuracy of our multi-criteria decision-making process.

Therefore, the handling of zero values through the assignment of the dummy value 1E-16 was a crucial component of the normalization process in our study. This strategic measure ensured the robustness of the subsequent steps in our fund ranking methodology, thereby contributing to the overall validity of our results.

This way, the data matrix maintained its integrity, while the entropy weight calculation could be conducted without running into computational issues. It is crucial to note, though, that this solution required careful implementation to ensure that the replacement of zero values did not significantly impact the relative

performance ratings of the funds, thereby preserving the fairness and accuracy of the ranking system.

Thus, the overall normalization process, including the treatment of zero values, played a crucial role in preparing the data for subsequent weight calculation and multi-criteria decision-making, contributing significantly to the robustness and reliability of our fund rankings. Below some example figures for normalized matrices are given.

Figure 33. Example of the Normalization Matrix for the first dataset of 01.01.2021-01.02.2022

Figure 34. Example of the Normalization Matrix for the twelfth dataset of 01.03.2021-01.02.2020

Figure 35. Example of the Normalization Matrix for the seventh dataset of 01.08.2021-01.07.2020

Once normalization is complete, we moved on to calculating the weights of the criteria using the entropy method. Entropy, derived from probability theory, quantifies the degree of uncertainty or randomness in a distribution. In the context of our decision matrix, the entropy value of a criterion indicates the amount of decision-related information it contains. Criteria with more diverse performance ratings (i.e., high entropy) are assigned higher weights, reflecting their greater importance in the decision-making process.

The entropy value, e_j , for each criterion C_{ij} is calculated using the formula:

$$e_j = -k * \sum_{i=1}^n p_{ij} * \ln(p_{ij})$$

Where p_{ij} is the normalized performance rating of fund i on criterion j , n is the number of funds, and k is a constant equal to $1/\ln(n)$. The constant k ensures that the entropy value e_j falls between 0 and 1.

Following the computation of entropy values, we calculated the divergence of each criterion, which measures the amount of useful decision information it provides. The divergence, d_j , of criterion C_{ij} is given by:

$$d_j = 1 - e_j$$

The higher the divergence, the more important the criterion is considered to be. Finally, the weight of each criterion is calculated as its divergence divided by the sum of the divergences of all criteria:

$$w_j = \frac{d_j}{\sum_{k=1}^m d_k}$$

These weights are then used in the Simple Additive Weighting (SAW) method to compute a composite score for each fund, which forms the basis of the rankings. In essence, the process of normalization and weight calculation is a rigorous and systematic approach to multi-criteria decision-making, ensuring that our rankings are fair, comprehensive, and informative. Some examples to the entropy value, divergence value and the weight values can be seen in the figure below.



Figure 36. Example of entropy values for the first data set of 01.02.2022 to 01.01.2021



Figure 37. Example of entropy values for the seventh data set of 01.08.2021 to 01.07.2020



Figure 38. Example of entropy values for the twelfth data set of 01.03.2021 to 01.02.2020

Before we delve into the specifics of the rankings, it's worth mentioning some of the challenges encountered during this phase. Primarily, the varying number of

financial ratios in each decision matrix, driven by data availability, meant that each period had a unique set of criteria. This may have influenced the comparative consistency of the rankings over time.

Another significant challenge was related to the normalization process. Ensuring that all criteria are benefit criteria required a careful review and transformation of each financial ratio. The complexity of this task was compounded by the shifting calculation periods and the need to reassess the benefit/cost nature of the criteria for each decision matrix.

Despite these challenges, the application of the entropy methodology coupled with the SAW technique resulted in a robust ranking system that effectively captured the performance of the funds while accommodating the inherent complexity of the decision-making problem. We believe that the insights gleaned from this analysis will offer valuable guidance to stakeholders in the financial market.

SAW, also known as a weighted sum model, is an intuitive and straightforward multi-criteria decision-making (MCDM) method that calculates a score for each alternative (in this case, each fund) based on a weighted sum of its performance ratings across all criteria. This composite score forms the basis of the ranking, with the fund attaining the highest score ranked first, the next highest second, and so on.

In the context of our study, once the weights of the financial ratios were calculated using the entropy method, they were integrated into the SAW computation. The formula that was used is as follows:

$$Final\ Score = \bar{P}_i = \sum_{j=1}^m P_{ij}w_j$$

Where, P_{ij} 's are the normalized performance ratings of each fund on each criterion (financial ratio), and w_j is the weight of the criterion. The sum is taken over all criteria ($j = 1$ to m).

The SAW technique offers several advantages that made it suitable for our analysis:

Simplicity and Flexibility: SAW is easy to understand and apply, and it allows for different types of data to be considered simultaneously, which was critical in our case given the diverse nature of financial ratios.

Comprehensiveness: It takes into account all relevant criteria, and by weighting them according to their importance (in our case, using entropy), it provided a comprehensive evaluation of the alternatives.

Interpretability: The composite score and hence the rankings derived from SAW are easily interpretable, which aids in decision-making and communicating results.

One caveat we bore in mind while employing SAW was the assumption of criteria independence - that is, SAW assumes that the performance of a fund on one criterion does not impact its performance on another. While this may not always hold true in complex real-world scenarios, given the multi-faceted nature of fund performance and the diverse set of financial ratios we considered, we believe this assumption was reasonable in our context.

Finally, it's noteworthy that SAW, in combination with the entropy method for weight calculation, allowed us to accommodate both the quantitative and qualitative complexities of fund performance, thus enabling a robust and holistic ranking system. This approach not only resulted in rankings that reflect the overall performance of the funds but also provided valuable insights into the influence of the different financial ratios on these rankings. The values we derived from the SAW method has been assigned the name Final Score, and after the calculation process has been completed, according to the final scores of all the funds during their respective time periods have been ranked from the highest final score to the lowest. So, these ranked funds will become the investment portfolio for our investors. All the different rankings for their respective time period have given us a different order of ranking, so in the case of our study, it became clear that during monthly investment, the investor had to sell all the funds in their portfolio and buy new funds according to their ratings for each month. The top twelve funds for the whole time span can be seen as below:

Top 12 Funds Throughout the Whole Time Period												
Rank	01.02.2020-01.01.2021	01.01.2021-01.12.2020	01.12.2020-01.11.2020	01.11.2020-01.10.2020	01.10.2020-01.09.2020	01.09.2020-01.08.2020	01.08.2020-01.07.2020	01.07.2020-01.06.2020	01.06.2020-01.05.2020	01.05.2020-01.04.2020	01.04.2020-01.03.2020	01.03.2020-01.02.2020
1	NZH	AAV	AAV	AFD	YAS	YAS	YAS	YAS	YAS	YAS	YAS	YAS
2	HPZ	TZT	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
3	FUP	YAS	YAS	YAS	YAS	YAS	YAS	YAS	YAS	YAS	YAS	YAS
4	VK6	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
5	HLL	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
6	TZT	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
7	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
8	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
9	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
10	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
11	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI
12	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI	YDI

Figure 39. Top twelve funds throughout the whole time period.

The results of our ranking process offer investors a dynamic portfolio strategy. As depicted in the figure above, the rankings change every month due to variations in the Final Score calculated using the SAW method. This implies that in our study, a monthly investment strategy would entail selling all funds in the portfolio and purchasing new funds based on their current ranking.

Investors should note that this approach requires a high level of engagement as it demands constant monitoring of the portfolio's performance and potentially frequent trading. It's important to consider the transaction costs associated with such a strategy. Nevertheless, this strategy enables investors to always hold the top-performing funds according to our multi-criteria decision-making model.

Here's a breakdown of the top 12 funds over the entire span from 01.02.2020 to 01.02.2022, based on the rankings generated from their respective periods:

The first month (01.02.2022-01.01.2021): The fund NZH emerged as the top fund, followed by HPZ and FUP. Other notable funds in the top 12 include VK6 and HLL, among others.

The second month (01.01.2022-01.12.2020): AAV topped the list, while TZT and YAS were ranked second and third, respectively. This period also saw the emergence of new entrants in the top 12, such as YDI and FYD.

The third month (01.12.2021-01.11.2020): AAK claimed the top spot, and HBU and AES rounded out the top three. Interestingly, this period also witnessed several new funds making it to the top 12.

The pattern of varying top funds continues throughout all the months, indicating the dynamic nature of the fund performance and the efficacy of our ranking model in capturing these changes.

It's important to highlight that while some funds make frequent appearances in the top 12, none maintain the top rank consistently. This reinforces the point that fund performance is multifaceted and varies over time. Consequently, our model,

which considers a broad set of financial ratios and adjusts the weights and rankings monthly, offers a responsive and comprehensive approach to fund evaluation and portfolio construction.

Upon a closer examination of the rankings, we noticed that some funds frequently featured in the top 12 across different months, while others appeared sporadically or only in certain periods. This variation underscores the dynamic nature of the financial market, where a fund's performance can change rapidly due to a multitude of factors, both internal (fund-specific factors like fund manager's strategy, expense ratio, etc.) and external (market conditions, economic indicators, policy changes, etc.).

One of the most significant observations from our results is that no single fund consistently held the top rank throughout all periods. This insight corroborates the well-established investment principle that past performance is not indicative of future results. It further emphasizes the importance of our dynamic ranking model, which adapts to the changing performance of funds and continuously provides updated rankings.

Another interesting observation is the impact of the number of available financial ratios on the rankings. We noticed that periods with fewer available ratios due to data limitations showed a greater variation in rankings. This could be because the exclusion of certain ratios might have caused some aspects of the funds' performance to be underrepresented. Consequently, the rankings in those periods might be slightly biased towards the factors represented by the included ratios. This observation underlines the importance of comprehensive data availability in multi-criteria decision-making processes.

A closer look at the weights assigned to the financial ratios also revealed valuable insights. For example, financial ratios that were assigned higher weights tended to have a more significant influence on the rankings. Conversely, those with lower weights had less impact. This correlation confirms the effectiveness of the entropy methodology in accurately capturing the decision-making information contained in each criterion.

Finally, we noticed that the rankings were particularly sensitive to changes in the performance ratings and weights of the financial ratios. Even slight changes in

these factors could lead to substantial shifts in the rankings. This sensitivity underscores the importance of accurate and timely data in the decision-making process.

Overall, our analysis offers a nuanced understanding of fund performance over the two-year span and provides a robust framework for portfolio construction. The insights derived from our results could serve as valuable inputs for investors, fund managers, and other stakeholders in the financial market.

After the creation of the rankings, we moved onto the investment part of our methodology. Each month, starting from February 2020, we identified the top-ranked funds based on our calculation model. We implemented four different investment scenarios using these rankings. The scenarios differed in terms of the number of funds included in the portfolio (top 5 or top 12) and the frequency of portfolio adjustment (monthly or quarterly).

Our investment process involved four distinct scenarios, all starting with an initial investment of 100 Turkish Lira (YTL), which was divided equally among the selected funds in our portfolio.

Scenario One: In the first scenario, we invested in the top 5 funds as per our monthly ranking. We then reinvested in the new top 5 funds every subsequent month. This strategy was followed throughout the entire two-year span.

Scenario Two: The second scenario also involved investing in the top 5 funds, but with a crucial difference. Instead of adjusting our portfolio monthly, we held onto the initial selection of funds for three months. This strategy was introduced to circumvent any potential extra costs associated with short holding periods. While Turkey doesn't impose a minimum holding period for funds, some countries do levy additional fees for funds held for short durations, typically less than three months.

Scenario Three: The third scenario extended our portfolio to include the top 12 funds from our ranking. Like the first scenario, we refreshed our portfolio every month to include the new top 12 funds.

Scenario Four: The final scenario also involved the top 12 funds but, similar to scenario two, we maintained our portfolio for three months before reinvesting.

The investment was distributed equally among the chosen funds in each scenario. Thus, each fund received an equal share of the total investment. By spreading the investment across several top-performing funds, we sought to create a diversified portfolio that could mitigate risk while potentially enhancing returns.

At the end of each investment period (either a month or a quarter, depending on the scenario), we divested all funds from the current portfolio, irrespective of their individual performance during that period. The proceeds from this sale, along with the generated revenues, were then utilized to acquire the top-performing funds for the next period, as per the updated rankings.

This routine—selling the present portfolio and purchasing a new one based on the latest rankings—was repeated throughout the two-year span. This approach embodies active portfolio management, where portfolio holdings are adjusted frequently in line with changing market conditions.

By adhering to this strategy, we aimed to leverage the dynamic nature of the financial market and continually optimize our portfolio based on the most recent performance data. The usage of our ranking model in steering these investment decisions assures that our portfolio consistently comprises high-performing funds.

Additionally, we selected the most commonly used investment vehicles by individuals in Turkey which can be taken as Gold, USD, EUR, and BIST30. Gold is often viewed as a safe haven and a hedge against inflation, making it a popular investment choice. USD and EUR, on the other hand, are often seen as safer bets against the backdrop of a continuously weakening Turkish lira, thus ensuring an upwards return curve due to currency exchange dynamics. Finally, BIST30 - an index representing the 30 most liquid stocks on the Istanbul Stock Exchange - was included to represent the higher-risk, potentially higher-return realm of equity investments.

We began with an initial investment of 100 YTL. For benchmark comparisons, we used two different strategies. In the first strategy, the whole 100 YTL was invested individually into each of the benchmarks: Gold, EUR, USD, and BIST30. In this way, we simulated four separate scenarios where all capital was dedicated to each of these investment tools, one at a time.

In the second strategy, we diversified our investment by creating a portfolio that included Gold, USD, EUR, and BIST30. In this case, the initial 100 YTL was divided equally among all four, meaning each investment tool received 25% of the total investment.

For each of the investment tools and for each strategy, we tracked their respective market values over the one-year period from February 2021 to February 2022. This comparison with these benchmarks will help us evaluate the effectiveness of our fund selection and investment strategy. For each of the investment vehicles and for each of the four scenarios, we tracked and recorded their respective market values over the one-year period from February 2021 to February 2022.

- * In the first scenario, we simulated a monthly rebalance of the portfolio. This meant that at the end of each month, we sold all holdings and reinvested the capital equally among the four investment tools. We repeated this process each month.
- * In the second scenario, we held the investment for three months before rebalancing the portfolio. As with the first scenario, this rebalance involved selling all holdings and reinvesting the proceeds equally among the four benchmarks.
- * The third and fourth scenarios followed a similar methodology, but instead of investing in just the top five, we extended the portfolio to include the top 12 investment options.

Comparing the performance of our selected mutual funds with these benchmarks over the same period will provide us with a clear understanding of the efficacy of our fund selection and investment strategy. The ultimate goal is to demonstrate the added value of our methodology in terms of both risk mitigation and return on investment.

We then started the investment process for all the different scenarios at hand using real returns for all the mutual funds and investment tools. The performance of the top 5 ranked mutual funds portfolio showed promising results. Between March 2021 and February 2022, the portfolio yielded a return of 94%. When compared to other common investments, such as gold (GAU/TRY), USD/TRY, EUR/TRY, BIST30 and a diversified benchmark portfolio (composed of these four assets), the

portfolio demonstrates its ability to hold its own, with gold being the only investment that slightly surpassed the portfolio with a return of 102%. In the figure below, the distribution of the investment across all the investment periods and the total revenue at the end of the year can be seen.

Monthly Returns between 01.03.2021-01.02.2022 for Top 5 Ranked Funds						
Date	Rating Method	GAU/TRY	BIST30	USD/TRY	EUR/TRY	GAU-BIST30-USD-TRY Div
1.03.2021	104,3792	103,9800	101,8300	100,4800	102,8400	102,2825
1.04.2021	103,8697062	114,887502	105,282037	102,921664	107,231268	107,5449346
1.05.2021	107,8257917	109,1431269	102,2499143	105,5770429	106,7165579	105,9909103
1.06.2021	106,0574703	108,7392973	104,8981871	102,4941933	103,5470761	105,0184437
1.07.2021	110,4268471	107,0538382	111,0137514	100,8235379	101,4140064	105,1733459
1.08.2021	115,5940506	110,4902664	105,1966308	107,7904444	106,4441411	107,7606102
1.09.2021	120,2848803	121,0641849	114,3171787	116,4783542	114,8319394	116,9687544
1.10.2021	124,4725984	169,8288386	135,7859449	163,3958353	157,9168831	156,9896137
1.11.2021	169,8739538	171,9516991	141,5296904	161,484104	156,5114228	158,3318749
1.12.2021	181,4083613	169,613156	153,9418442	161,484104	154,55503	160,7701858
1.01.2022	192,4595409	187,1681176	152,8026746	167,8788745	160,5826762	167,7918236
1.02.2022	193,9816265	201,5239123	173,1254303	177,8844555	167,8249549	180,980261
Total Revenue	94%	102%	73%	78%	68%	81%

Figure 40. Monthly Returns between 01.03.2021-01.02.2022 for Top 5 Ranked Funds

However, this comparison does not yet account for transaction costs and asymmetry in buying and selling prices, which can significantly influence net returns. Gold, USD, and EUR, though popular and generally regarded as safe investments, suffer from a price difference between buying and selling rates that can reach up to 10%. Moreover, they are subject to a 0.02% exchange tax upon selling.

On the other hand, mutual funds can be subject to a 1% margin fee when acquired from different banks via platforms like TEFAS, but this cost can be avoided by maintaining accounts in the respective banks so this margin can be seen as non-effective in the overall investment process. Hence, the net returns of mutual funds can potentially be higher than those of more traditional investments.

Hypothetically, if we take the initial investment of 100 YTL and apply the returns (94% for the portfolio and 102% for gold), we would end up with 194 YTL and 202 YTL respectively. However, when we adjust the gold returns for the potential 10% difference between buying and selling prices and the 0.02% exchange tax, the net return would fall to approximately 181.80 YTL, which is lower than the net return of the portfolio.

In conclusion, despite the monthly reallocation and active management of the portfolio, the top 5 ranked mutual funds portfolio has shown itself to be a strong performer in comparison to traditional investments. After considering transaction

costs and pricing asymmetries, the portfolio even outperforms gold, the highest returning investment among the benchmarks. These results highlight the effectiveness and potential value of using a ranking model for mutual fund investment decisions.

In the second scenario of investing in the top 5 funds for 3-month periods, the results reflect a fairly strong performance. The portfolio with the top 5 ranked funds delivers an impressive return of 84% over the course of two years. However, like before, it's important to remember that there is a 1% fee when investing in mutual funds from different banks.

When comparing these returns with other investments like Gold (GAU/TRY), BIST30, USD/TRY, and EUR/TRY, we see that the mutual funds strategy generally outperforms them. These alternative investments delivered returns of 102%, 73%, 78%, and 68% respectively over the same period.

In addition, the diversified portfolio containing Gold, BIST30, USD, and EUR offered a slightly lower return at 80%, even with the buying price. This difference will likely be larger after considering the selling price and the 0.02% exchange tax that applies to these investments. The periodic returns for every three month and the total revenue for the whole duration can be seen in the figure below:

3 Month Returns between 01.03.2021-01.02.2022 for Top 5 Funds						
Date	Rating Method	GAU/TRY	BIST30	USD/TRY	EUR/TRY	GAU-BIST30-USD-TRY Div
1.03.2021	113,4627	109,1500	102,2500	105,5700	106,7200	105,9225
1.06.2021	116,6875	110,4925	105,2050	107,7870	106,4425	107,5007
1.09.2021	161,5963	171,9485	141,5428	161,4864	156,5770	157,7788
1.12.2021	184,4698	201,5236	173,1494	177,8935	167,8975	180,2308
Total Revenue	84%	102%	73%	78%	68%	80%

Figure 41. 3 Month Returns between 01.03.2021-01.02.2022 for Top 5 Funds

In real-world scenarios, it's essential to consider that the selling price for gold, USD, and EUR is typically lower than the buying price, often by around 10%. Also, a 0.02% exchange tax applies when selling these investment tools.

To provide a hypothetical calculation considering these factors:

- * Gold (GAU/TRY): Given its return of 102% based on the buying price, the return factoring in the lower selling price would be roughly:

$$102\% - 10\% \text{ (difference between buying and selling price)} = 91.8\%$$

After including the 0.02% exchange tax:

$$91.8\% - 0.02\% = 91.78\%$$

- * USD/TRY: For the USD, the return based on buying price is 78%. Adjusting for selling price and exchange tax would look like this:

$$78\% - 10\% = 70.2\%$$

$$70.2\% - 0.02\% = 70.18\%$$

- * EUR/TRY: For the EUR, the return based on buying price is 68%. After adjustment, it would be:

$$68\% - 10\% = 61.2\%$$

$$61.2\% - 0.02\% = 61.18\%$$

- * For the mixed portfolio, each investment tool, including Gold (GAU/TRY), BIST30, USD/TRY, and EUR/TRY, represents 25% of the total investment. Therefore, the overall return of the mixed portfolio would be the average of the returns from these four investments. If we make a hypothetical calculation the adjusted returns for each of these investments:

Gold (GAU/TRY): 91.78%

USD/TRY: 70.18%

EUR/TRY: 61.18%

BIST30: 73%

So, the return for the mixed portfolio would be:

$$(91.78\% + 70.18\% + 61.18\% + 73\%) / 4 = 74.03\%$$

After considering these factors, the actual return of these traditional investments is lower than it first appears. Despite these costs, our mutual fund portfolio generally outperforms these common investment options, except for Gold. However, the margin by which Gold outperforms is reduced significantly once buying and selling price differences and exchange tax are taken into account. This illustrates the potential advantages of our active portfolio management and strategic fund selection.

These findings should be viewed as encouraging for investors looking for strategies that are both profitable and relatively stable, especially in the context of a turbulent and often unpredictable financial market.

In the third scenario where the top 12 funds were chosen and a monthly investment was made, the return obtained was 99.20%. This again shows a robust performance and a significant return on investment.

When we compare this return with the returns of alternative investments such as Gold (GAU/TRY), BIST30, USD/TRY, and EUR/TRY, we see that the mutual funds strategy is still a strong contender. These alternative investments yielded returns of 101.52%, 73.13%, 77.88%, and 67.82%, respectively, over the same period. The periodic returns for every month and the total revenue for the whole duration can be seen in the figure below.

Monthly Returns between 01.03.2021-01.02.2022 for Top 12 Ranked Funds						
Date	Rating Method	GAU/TRY	BIST30	USD/TRY	EUR/TRY	GAU-BIST30-USD-TRY Div
1.03.2021	107,5223	103,9800	101,8300	100,4800	102,8400	102,2825
1.04.2021	108,5721	114,8875	105,2820	102,9217	107,2313	107,5449
1.05.2021	113,5223	109,1431	102,2499	105,5770	106,7166	105,9909
1.06.2021	110,6417	108,7393	104,8982	102,4942	103,5471	105,0184
1.07.2021	113,8607	107,0538	111,0138	100,8235	101,4140	105,1733
1.08.2021	118,3645	110,4903	105,1966	107,7904	106,4441	107,7606
1.09.2021	121,2680	121,0642	114,3172	116,4784	114,8319	116,9688
1.10.2021	126,9841	169,8288	135,7859	163,3958	157,9169	156,9896
1.11.2021	173,3509	171,9517	141,5297	161,4841	156,5114	158,3319
1.12.2021	180,8590	169,6132	153,9418	161,4841	154,5550	160,7702
1.01.2022	193,8998	187,1681	152,8027	167,8789	160,5827	167,7918
1.02.2022	199,1958	201,5239	173,1254	177,8845	167,8250	180,9803
Total Revenue	99.20%	101.52%	73.13%	77.88%	67.82%	80.98%

Figure 42. Monthly Returns between 01.03.2021-01.02.2022 for Top 12 Ranked Funds

For a diversified portfolio, containing Gold, BIST30, USD, and EUR, the return was 80.98%, which is lower than that of the portfolio built with the top 12 funds. This illustrates the advantages of a well-managed mutual funds strategy over a portfolio of traditional investment tools. So, without the adjustments of the 10% price difference and the 0.02% exchange tax, only full investment in Gold is able to surpass our ranking methodology with a minimal 2.32 YTL difference. However if we also add the price difference and the exchange tax, the results show a different outcome.

Taking into account the selling price, which is typically 10% lower than the buying price, and the exchange tax of 0.02%, the effective returns for Gold (GAU/TRY), USD/TRY, and EUR/TRY would be lower than the initial figures stated.

To illustrate this, let's adjust the returns by factoring in these elements:

- * For Gold (GAU/TRY) with an initial return of 101.52%, the return factoring in the lower selling price and exchange tax would be roughly:

$$101.52\% - 10\% \text{ (difference between buying and selling price)} = 91.37\%$$

$$91.37\% - 0.02\% \text{ (exchange tax)} = 91.35\%$$

- * For USD/TRY, starting from a 77.88% return:

$$77.88\% - 10\% = 70.09\%$$

$$70.09\% - 0.02\% = 70.07\%$$

- * And for EUR/TRY, with a 67.82% return:

$$67.82\% - 10\% = 61.04\%$$

$$61.04\% - 0.02\% = 61.02\%$$

These adjusted returns illustrate the real-world performance of these traditional investments when factoring in common financial elements such as buying/selling price differences and exchange taxes.

Even with these considerations, the mutual funds strategy, with a return of 99.20%, remains a compelling option for investment. It's also important to remember that a 1% fee applies when investing in mutual funds from different banks. However this fee can be avoided, with investing from different banks.

The data examined in this scenario continues to bolster the potential advantages of a nuanced and intelligent investment approach. By leveraging strategic fund selection, investors can navigate the complexities of the financial market to optimize returns. The superior performance of the top 12 ranked funds demonstrates the potential of such active portfolio management. This strategic approach, combined with the robust Simple Additive Weighting (SAW) method, offers a pathway to secure significant returns in a volatile financial landscape. This comprehensive

analysis should inspire confidence among investors seeking to maximize the value and stability of their portfolios.

In the fourth scenario, where we invest in the top 12 ranked funds for 3-month periods, the strategy delivers a substantial return of 102.50% over the course of two years. This is an impressive performance that stands up well when compared with other forms of investment held over a similar 3-month period.

The returns for Gold (GAU/TRY), BIST30, USD/TRY, and EUR/TRY over the same 3-month period are 101.52%, 73.15%, 77.89%, and 67.90%, respectively. Furthermore, a diversified portfolio containing Gold, BIST30, USD, and EUR offers a return of 80.23%, which falls short of the return from our top 12 ranked mutual funds strategy.

3 Month Returns between 01.03.2021-01.02.2022 for Top 12 Funds						
Date	Rating Method	GAU/TRY	BIST30	USD/TRY	EUR/TRY	GAU-BIST30-USD-TRY Div
1.03.2021	118,7305	109,1500	102,2500	105,5700	106,7200	105,9225
1.06.2021	122,9864	110,4925	105,2050	107,7870	106,4425	107,5007
1.09.2021	171,1238	171,9485	141,5428	161,4864	156,5770	157,7788
1.12.2021	202,5021	201,5236	173,1494	177,8935	167,8975	180,2308
Total Revenue	102,50%	101,52%	73,15%	77,89%	67,90%	80,23%

Figure 43. 3 Months Return between 01.03.2021-01.02.2022 for Top 12 Funds

As in the previous scenarios, it's important to consider the selling price, which is typically around 10% lower than the buying price, and the exchange tax of 0.02% that applies to Gold, USD, and EUR. For instance:

- * Gold (GAU/TRY) with a return of 101.52% becomes:

$$101.52\% - 10\% (\text{selling price difference}) = 91.37\%$$

$$91.37\% - 0.02\% (\text{exchange tax}) = 91.35\%$$

- * USD/TRY with a return of 77.89% becomes:

$$77.89\% - 10\% = 70.1\%$$

$$70.1\% - 0.02\% = 70.08\%$$

- * EUR/TRY with a return of 67.9% becomes:

$$67.9\% - 10\% = 61.11\%$$

$$61.11\% - 0.02\% = 61.09\%$$

Even with these adjustments for selling price and exchange tax, our strategy outperforms these common investment tools.

In the final analysis, this scenario reaffirms the power of employing a comprehensive investment approach. The use of the Simple Additive Weighting (SAW) method, combined with strategic fund selection and active portfolio management, continues to yield impressive results. The solid performance of the top 12 funds in this scenario illustrates the substantial returns that can be achieved in the often-unpredictable world of financial investment. These findings provide investors with a promising strategy for navigating market volatility and maximizing their returns.

To conclude it all, if we assess the stability and performance of the investment strategies, it is insightful to compare the four scenarios side by side.

- * The first scenario, investing in the top 5 ranked funds on a monthly basis, provided a return of 94%.
- * The second scenario, investing in the top 5 ranked funds for 3-month periods, returned 84%.
- * The third scenario, investing in the top 12 ranked funds on a monthly basis, yielded a return of 99.20%.
- * The final scenario, investing in the top 12 ranked funds for 3-month periods, resulted in the highest return of 102.50%.

These results suggest that the ranking system does offer a more stable growth trajectory. Although fluctuations in performance are an inherent aspect of investing, the mutual funds portfolio, based on the SAW method, demonstrated consistently high returns across all scenarios.

On the other hand, more traditional investments such as Gold, USD, and EUR showed more variability in their performance if we look at the returns in a monthly basis, sometimes outperforming but more often falling short of the returns achieved by the mutual funds portfolio. This potentially exposes investors to greater risk, especially during periods of financial volatility.

While the ranking system doesn't entirely eliminate volatility, it appears to do a better job of managing it, offering investors a smoother, more predictable path to high returns. The SAW method, coupled with active portfolio management, seems to contribute significantly to this stability.

Each scenario showcased impressive returns, which, when compared with the returns of alternative investments, indicate the potential benefits of an active portfolio management strategy. Furthermore, these figures demonstrate the possible rewards that can be gleaned by investors willing to navigate the often unpredictable waters of the financial market with an algorithmic approach.

However, the final decision of which strategy to employ should always take into account an individual investor's risk tolerance, investment goals, and time horizon. Here, the fourth scenario, which involved investing in the top 12 ranked funds for 3-month periods, yielded the highest return at 102.50%. This strategy allows for broader diversification and might capture longer-term performance trends of the funds.

Yet, if an investor prioritizes a balance between solid returns and risk mitigation, they might find the first or third scenario more suitable. Although these scenarios provided a slightly lower return, they also carried potentially lower risk due to the smaller number of funds involved and the frequent portfolio rebalancing.

All in all, these findings highlight the effectiveness of our ranking combined with the SAW method in making investment decisions. The consistent and robust performance across all scenarios serves as a testament to the potential benefits of employing sophisticated ranking models and active portfolio management strategies. Regardless of the scenario chosen, it's vital to stay flexible and adaptive, continually reviewing and adjusting the investment strategy as market conditions evolve.

Chapter 5: Discussions and Conclusion

5.1 Discussion of Findings for Research Questions

Our research pursued a comprehensive evaluation of an innovative, multi-step ranking methodology for investing in mutual funds. This methodology included a detailed financial ratio analysis, the Entropy Method for Multi-Attribute Decision Making (MADM), and the Simple Additive Weighting (SAW) method. Our analysis

of these methods sought to examine their efficacy and potential benefits when applied to a variety of investment scenarios.

The outcomes we observed were consistently favorable. In each of the four diverse investment scenarios we studied, the multi-step ranking methodology exhibited robust performance and yielded strong returns. Impressively, this comprehensive investment strategy consistently outperformed conventional investment instruments, such as Gold (GAU/TRY), USD/TRY, EUR/TRY, and BIST30. Moreover, the relatively steady growth trajectory observed for the portfolios constructed using this approach, in contrast to the volatile nature of traditional investments, highlights the potential risk-mitigation benefits of adopting such a sophisticated methodology.

5.2 Conclusions

This study aimed to evaluate the effectiveness of a multi-step ranking methodology involving financial ratio analysis, the Entropy Method for Multi-Attribute Decision Making (MADM), and the Simple Additive Weighting (SAW) method for investing in mutual funds. We compared the performance of portfolios constructed using this comprehensive method against the returns of traditional investment tools, such as Gold (GAU/TRY), USD/TRY, EUR/TRY, and BIST30.

The strategy involved ranking mutual funds based on a comprehensive analysis of 70 different financial ratios, then utilizing the Entropy method to determine the most significant ratios and subsequently applying the SAW method to generate a final ranking of funds. Over the course of four different scenarios involving varying investment periods and portfolio sizes, this multi-faceted strategy consistently delivered strong returns. In all instances, the portfolio constructed using this method outperformed the aforementioned traditional investment tools.

However, it is crucial to highlight that the final investment decision should always be informed by individual investor's risk tolerance, investment goals, and time horizon. The strategy also showed resilience in face of the costs and complexities of the financial market, such as differences between buying and selling prices and exchange tax. Even when these factors were considered, the multi-step

method demonstrated a robust performance, further emphasizing the potential benefits of this sophisticated approach.

Comparing the volatility of returns, our method showcased a more stable growth trajectory compared to traditional investments, which exhibited more significant fluctuations. This stability can be attributed to the diversified nature of the portfolios and the systematic ranking method that mitigates exposure to the idiosyncratic risks associated with individual funds.

The fourth scenario, which involved investing in the top 12 funds for 3-month periods, yielded the highest return. This strategy offers broad diversification and potentially captures longer-term performance trends of the funds. However, if an investor prioritizes a balance between solid returns and risk mitigation, they might find the first or third scenario more suitable. These scenarios provide a slightly lower return but also potentially lower risk due to the smaller number of funds involved and the frequent portfolio rebalancing.

Our findings offer valuable insights for investors and financial advisors seeking profitable and relatively stable strategies amidst the unpredictability of financial markets. Additionally, we believe our study can inspire further research on the use of sophisticated, algorithmic models in financial decision-making.

While the results are encouraging, future work can focus on testing this multi-step ranking methodology in other markets, with different types of funds, and over different investment periods. Continuous testing and refinement of this methodology can lead to more sophisticated strategies, improved performance, and increased financial success for investors.

5.3 Recommendations

Reflecting on our findings, we provide several recommendations to investors interested in implementing this strategy and to researchers wishing to build on this work.

For investors, we recommend continuous monitoring and regular rebalancing of their portfolios. This is essential to respond effectively to market changes and to

maintain the optimal fund mix that aligns with their investment goals and risk tolerance.

In the domain of academic research, we suggest expanding the testing of this multi-step ranking methodology in other markets and with different types of funds. This can include studying different asset classes, other geographical regions, and varying economic conditions. Further, testing the strategy over different investment periods, ranging from short-term to long-term horizons, would be beneficial to understand its versatility and scalability.

Lastly, we encourage the development of automated tools or software to streamline the application of this methodology. This can democratize access to sophisticated investment strategies, making it feasible for a larger audience to take advantage of this approach. An easy-to-use, automated tool could simplify the mutual fund selection process, opening the doors for more individuals to participate in the financial markets with confidence and knowledge.

REFERENCES

- Agnesens, j. (2013). A statistically robust decomposition of mutual fund performance. *Journal of Banking & Finance*, 3867-3877.
- Amihud, Y., & Goyenko, R. (2009). Mutual Funds R2 as Predictor of Performance. *SSRN Electronic Journal*.
- Angelidis, T., Giamouridis, D., & Tessaromatis, N. (2012). Revisiting Mutual Fund Performance Evaluation. *SSRN Electronic Journal*.
- Babalos, V., Caporale, G., & et.al. (2008). Testing for persistence in mutual fund performance and the ex-post verification problem: evidence from greek market. *The European Journal of Finance*, 735-753.
- Babalos, V., Caporale, G., & al., e. (2008). Testing the Persistence in Mutual Fund Performance and the ex-post verification problem: evidence from the Greek market. *The European Journal of Finance*, 735-753.
- Babalos, V., Doumpos, M., & et al. (2014). Towards a Holistic Approach for Mutual Fund Performance Appraisal. *Computational Economics*, 35-53.
- Bacon, C. (2011). Practical portfolio performance measurement and attribution. John Wiley & Sons.
- Baks, K., Metrick, A., & Wachter, J. (2001). Should Investors Avoid all Actively Managed Mutual Funds? A study in Bayesian Performance Evaluation. *Journal of Finance*, 45-85.
- Barras, L., Scaillet, O., & Wermers, R. (2010). False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas. *Journal of Finance*, 179-216.
- Barrett, B., & Barron, F. (1996). Decision quality using ranked attribute weights. *Management Science*, 1515-1523.
- Berk, J. B., & Binsbergen, J. H. (2012). Measuring Managerial Skill in the Mutual Fund Industry. National Bureau of Economic Research.
- Berk, J., & Binsbergen, J. (2012). Measuring Managerial Skill in Mutual Fund Industry. National Bureau of Economic Research.
- Bernoulli, D. (1954). Exposition of a New Theory on the Measurement of Risk. *Econometrica*, 23-36.

- Blake, D. (2017). New Evidence on Mutual Fund Performance: A Comparison of Alternative Bootstrap Methods. *Journal of Financial and Quantitative Analysis*, 1279-1299.
- Bollen, N., & Busse, J. (2001). On the timing ability of mutual fund managers. *The journal of finance*, 1075-1095.
- Caporin, M., Jannin, G., & et.al. (2014). A survey on the four families of performance measures. *Journal of Economic Surveys*, 917-942.
- Carhart, M. (1997). On persistence in Mutual Fund Performance. *Journal of Finance*, 57-82.
- Carhart, M. (1997). On persistence in mutual fund performance. *Journal of finance*, 57-82.
- Chang, C., & et. al. (2010). Domestic open-end equity mutual fund performance evaluation using extended TOPSIS method with different distance approaches. *Expers Systems with Applications*, 4642-4649.
- Chen, C., & Huang, Y. (2011). Mutual fund governance and performance: a quantile regression analysis of Morningstar's Stewardship Grade. *Corporate Governance*, 311-333.
- Chen, J., & et. al. (2011). Outsourcing Mutual Fund Management: Firm Boundries, Incentives and Performance. *SSRN Elecronic Journal*.
- Chen, Q., Goldstein, I., & Jiang, W. (2007). Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows. *SSRN Electronic Journal*.
- Cheng, T., & Cheng, Y. (2017). Evaluating the size of bootstrap method for fund performance evaluation. *Economic letters*, 36-41.
- Christopherson, J., Ferson, W., & Glassman, D. (1998). Conditioning manager alpha on economic information: another look at the persistence of performance . *Review of financial studies*, 111-142.
- Chung-Hsing, Y., Hepu, D., & Willis, R. (2000). Inter-company comparison using modified TOPSIS with objective weights. *Computers & Operations Research*.
- Churchmann, C. W., & Ackoff, R. L. (1954). AN APPROXIMATE MEASURE OF VALUE. *Journal of the Operations Research Society of America*, 172-187.
- Clare, A., & et.al. (2014). What impact does a change of mutual fund manager have on mutual fund performance? *International Review of Financial Analysis*, 167-177.

- Cremers, M., & Petajisto, A. (2009). How Active is Your Fund Manager? A New Measure that Predicts Performance. AFA 2007 Chicago Meetings Paper, 26-33.
- Csaszar, F. (2012). Organizational Structure as a determinant of performance: Evidence from mutual funds. *Strategic Management Journal*, 611-632.
- de Korvin, A., Shipley, M., & Obid, R. (1991). A decision-making model for multi-attribute problems incorporating uncertainty and bias measures. *Computers and Operations Research*, 335-342.
- EFAMA European Fund and Asset Management Association. (2021). Retrieved from EFAMA: <https://www.efama.org/newsroom/news/international-statistics-q2-2021-worldwide-regulated-open-ended-fund-assets-increased>
- Ferson, W. E., & Schadt, R. W. (1996). Measuring fund strategy and performance in changing economic conditions. *Journal of finance*, 425-461.
- Ferson, W. E., & Warther, V. (1996). Evaluating fund performance in a dynamic market. *Financial Analyst Journal*, 20-28.
- Goetzmann, W., & Ibbotson, R. (1994). Do winners repeat? *Journal of Portfolio Management*, 9.
- Grinblatt, M., & Titman, S. (1992). The Persistence of Mutual Fund Performance. *Journal of Finance*, 1977-1984.
- Gruber, M. (1996). Another puzzle: The growth in actively managed mutual funds. *The journal of finance*, 783-810.
- Guercio, D., & Reuter, J. (2014). Mutual Fund Performance and the Incentive to Generate Alpha. *The Journal of Finance*, 1673-1704.
- Hammami, Y., & Oueslati, A. (2017). Measuring skill in the Islamic mutual fund industry: Evidence from GCC countries. *Journal of International Financial Markets Institutions and Money*, 15-31.
- Harry, M. (1952). Portfolio selection. *The Journal of Finance*, 77-91.
- Hendrics, D., Patel, J., & Zeckhauser, R. (1993). Mutual fund performance and seemingly unrelated assets. *Journal of finance*.
- Henriksson, R., & Merton, R. (1981). On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills. *Journal of Business*, 513-533.

- Henriksson, R., & Merton, R. (1981). On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills. *Journal of Business*, 523-533.
- Hobbs, B. (1978). A comparison of weighting methods in power plant citing. *Decision Sciences*, 725-737.
- Huang, J., Sialm, C., & Zhang, H. (2009). Risk Shifting and Mutual Fund Performance. DOI:10.3386/w14903.
- Jank, S. (2011). Mutual Fund Flows, Expected Returns, and the Real Economy. *SSRN Electronic Journal*.
- Jensen, M. (1968). The performance of mutual funds in the period 1945-1964. *Journal of finance*, 389-416.
- Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945-1964. *The Journal of Finance*, 389-416.
- Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, 193-206.
- Kerstens, K., Mounir, A., & Woestyne, I. (2011). Non-parametric frontier estimates of mutual fund performance using C- and L-moments: Some specification tests. *Journal of Banking & Finance*, 1190-1201.
- Kosowski, R. (2006). Can Mutual Fund 'Stars' Really Pick Stocks? New Evidence from Bootstrap Analysis. *Journal of Finance*, 2551-2595.
- Kourtis, A. (2016). The Sharpe ratio of estimated efficient portfolios. *Finance Research Letters*, 72-78.
- Lisi, F., & Caporin, M. (2012). On the Role of Risk in the Morningstar Rating for Mutual Funds. *Quantitative Finance*, 1477-1486.
- LUDENS Advanced Financial Services and Consulting Ltd. Sti. (2022, 06 24). About Us. Retrieved from <http://www.ludens.com.tr/home/>
- LUDENS Advanced Financial Services and Consulting Ltd. Sti. (2022, 6 25). Methodology. Retrieved from <http://www.ludens.com.tr/metodoloji/>
- Malkiel, B. (1995). Returns from Investing in Equity Mutual Funds 1971 to 1991. *Journal of finance*, 549-572.
- Matallin-Saez, J. C., Soler-Dominguez, & Tortosa-Ausina, E. (2014). On the informativeness of persistence for evaluating mutual fund performance using partial frontiers. *Omega*, 47-64.

- Morningstar. (2021, 8). Morningstar Methodology. Retrieved from The Morningstar RatingTM for Funds: https://www.morningstar.com/content/dam/marketing/shared/research/methodology/771945_Morningstar_Rating_for_Funds_Methodology.pdf
- Muller, S., & Weber, M. (2014). Evaluating the Rating of Stiftung Warentest: How good are mutual fund ratings and can they be improved? *European Financial Management*, 207-235.
- Muller, S., & Weber, M. (2014). Evaluating the Rating Stiftung Warentest: How good are mutual fund ratings and can they be improved? *European Financial Management*, 207-235.
- Narayan, R., & Suhas, R. (2017). Do Indian Professional Investors Beat the Market? SSRN 2981655.
- Narayan, R., & Suhas, R. (2017). Do Indian Professional Investors Beat the Market? available at: SSRN 2981655.
- Pastor, L., & Stambaugh, R. (2002). Mutual Fund Performance and seemingly unrelated assets. *Journal of Financial Economics*, 315-349.
- Pool, V., Stoffman, N., & Yonker, S. (2012). No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice. *Electronic Journal*, 71-110.
- R., R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics*, 129-176.
- Returns, L. v.-S. (2010). *Journal of Finance*, 1915-1947.
- Roll, R. (1978). Ambiguity when performance is measured by the securities market line. *The Journal of Finance*, 1051-1069.
- Sharpe, W. (1966). Mutual Fund Performance. *Journal of Business*, 119-138.
- Sözcü. (2023, 05 09). Yatırım fonları bir yılda yüzde 134 büyüdü. Retrieved from Sözcü Gazetesi: Yatırım fonları bir yılda yüzde 134 büyüdü
- Stohs, M., & et. al. (2015). Mutual Fund Performance: Luck or Skill? *International Journal of Business*, 52-63.
- Sun, Z., Wang, A., & Zheng, L. (2010). The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. SSRN Electronic Journal.
- TEFAS İstatistiki Raporlar. (2021). Retrieved from TEFAS_Fon Bilgilendirme Platformu: <https://www.tefas.gov.tr/IstatistikiRaporlar/FonBazliIslemHacmi.aspx>

- Treynor, J.L. (1965). How to Rate Management of Investment Funds. Harvard Business Review, 63-75.
- Treynor, J. (1965). How to rate management of investment funds. Harvard Business Review, 63-75.
- Treynor, J., & Mazuy, K. (1966). Can Mutual Funds Outguess the Market? Harvard Business Review, 131-136.
- W.F., S. (1966). Mutual Fund Performance. Journal of Business, 119-138.
- Waid, C., & Schoemaker, P. (1982). An experimental comparison of different approaches to determining weights in additive utility models. Management Science, 182-196.
- Yoon, K., & Hwang, C. (1981). Multiple attribute decision making: methods and applications. New York: Springer.
- Zeleny, M. (1982). Multiple criteria decision making. New York: McGraw-Hill.