

Measuring the performance and asset allocation of robo-advisors in BRICS

Master of Commerce (50% Research) in Finance

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Declaration

I declare that this is my own unaided work. All work that is not my own has been duly acknowledged in the acknowledgements section or referenced in the text. It has been submitted for examination for the degree of Master of Commerce (50% Research) in Finance at the University of the Witwatersrand and has not been submitted for examination at any other institution.



29 February 2024

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Abstract

The financial industry has undergone some digital changes over the past decade. Financial technology (FinTech) is a result of this digital change and robo-advisors constitute FinTech in the wealth management space. The emergence of robo-advisors is a global phenomenon and, in this study, the performance and asset allocation of the robo-advisors from Brazil, Russia, India, China, and South Africa (BRICS) were measured. BRICS countries are one of the largest growing economies and provide international investors with diversification. The purpose of this study was to analyse if the recommended portfolios of the robo-advisor can perform similar to a benchmark and to explain the performance differences between the different recommended portfolios of the robo-advisors from each country using a returns-based style analysis. Furthermore, this study analysed the performance of robo-advisors before and after considering fees and the returns-based style analysis was also used to capture the exposure of each robo-advisor to mutually exclusive asset classes. The data included four robo-advisors in total with one robo-advisor from each country (a total of 62 portfolios) as there was a removal of the Russian EFTs due to the Russian-Ukraine war of 2022. The sample period was from 2015 to 2022 as most robo-advisors only became available after 2015. The performance tests that were performed were the Sharpe ratio, Jensen's alpha, Treynor ratio and Manipulation-proof performance measure. It is found that there are certain countries that have robo-advisors with portfolios that perform similar to the benchmark and do not outperform the benchmark and other countries that have portfolios that outperform the benchmark and the portfolios do not perform similar to the benchmark. Furthermore, it is found that performance differences can be explained by the investment style i.e., whether the portfolios have exposure to the same assets. The performance differences can also be explained by asset allocation in each portfolio based on uncorrelated assets.

Acknowledgements

In this acknowledgement section, I would first like to take the time to thank God, my supervisor, colleagues and most importantly my family and friends for their unwavering support and encouragement during one of the most difficult seasons of my life.

To my supervisor, you have been so understanding and gracious towards me, thank you. To my colleagues, thank you for believing in me and encouraging me. To my family and friends, words will never be enough to express my utmost gratitude towards you. You have never left my side. Thank you for believing in me until the very end and the emotional support you have provided me during this tough journey. I would also like to extend gratitude towards my late grandmother, I wish you were here to see this big milestone in my life. You would have been so proud of me.

And lastly, I give God all the glory and all the praise for getting me thus far. It is by Your Grace, mercy, and supernatural strength that I can hand in my research report.

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List of acronyms

BRICS	Brazil, Russia, India, China, and South Africa
CAPM	capital asset pricing model
ETFs	exchange-traded funds
FinTech	financial technology
MOEX	Moscow Exchange
MPPM	manipulation-proof performance measure
MPT	modern portfolio theory
PwC	PricewaterhouseCoopers

MEASURING THE PERFORMANCE AND ASSET ALLOCATION OF ROBO-ADVISORS IN BRICS

1 Introduction

1.1 Background and overview

The digital transformation of industries is driving improvements in business processes together with changes in customer experience and business models (Torno & Schildmann, 2020). In the financial sector, incumbents and new start-ups known as financial technology (FinTech) are competing in digitalisation and automation efforts to provide new ways to serve customers (Alt & Puschmann, 2016). Bates (2017) defined FinTech as a technology-enabled financial innovation that can create new business models, applications, processes or products that have significant implications for markets and financial institutions. Traditionally, financial advice in the wealth and asset management field involves human interactions and trust between the financial advisor and the customer (Torno *et al.*, 2021). However, these services are costly and are mostly accessible to individuals with a high net worth (Torno *et al.*, 2021). Therefore, to provide financial advice to retail investors at a lower cost, digital transformation has led to the development of robo-advisors which provide a much cheaper alternative (Sironi, 2016; Gomber *et al.*, 2018). Fisch *et al.* (2019) defined robo-advisors as "automated online services that use computer algorithms to provide financial advice and manage customers' investment portfolios". Robo-advisors work by assisting investors through an automated financial process and recommend a personalised portfolio based on risk preferences, investment goals and investment horizon (Sironi, 2016; Jung *et al.*, 2018). Furthermore, the robo-advisor monitors and rebalances the investor's portfolio to continue to match the investor's investment goals (Sironi, 2016; Jung *et al.*, 2018).

Robo-advisors are a global phenomenon (Puhle, 2019). *Betterment* is the first robo-advisor that was created in the United States in 2010 (Puhle, 2015). As of October 2023, Vanguard Digital Advisor is the largest robo-advisor with a \$228.2 billion asset under management (Nasr, 2024). It is estimated that by 2025 robo-advisors will manage US\$16 trillion worth of assets (Smith, 2020). This is greater than the asset under management of BlackRock, currently the world's biggest asset manager (Smith, 2020). The emergence of robo-advisors was delayed in the

Asia/Pacific region due to the shortage of exchange-traded funds (ETFs)¹ as robo-advisors use them to structure the recommended portfolios (Puhle, 2019). The robo-advisory field in South Africa is quite small and is often limited to banks, fund managers and financial advisors who use it within their own practices (Sarpong, 2020). Although robo-advisors are a growing phenomenon, the academic literature describing them is still rare. Puhle (2019) examined the performance of five German robo-advisors using a returns-based style analysis. The purpose of this research was to replicate Puhle (2019) in a Brazilian, Russian, Indian, Chinese, and South African context (BRICS). This is to explain the performance differences between the portfolios recommended by the robo-advisors in each specific country and determine if the portfolios recommended can provide similar performance to the benchmark.

BRICS countries are emerging markets and there is a low correlation between emerging market securities and developed markets (Watson & Seetharam, 2014). Grant Thornton International (2017) states that since BRICS countries are fundamentally different from an economic perspective, it is expected that the lower correlations of returns should exist. Thus, providing diversification benefits as some robo-advisors recommend portfolios with emerging markets. Furthermore, BRICS countries provided a larger sample size for this study.

1.2 Research objective

The first objective was to measure the performance of the different recommended portfolios by the robo-advisors in Brazil, Russia, India, China, and South Africa² and explain the performance differences between each recommended portfolio using a returns-based style analysis (Sharpe, 1992). Each robo-advisor had portfolios suited for investors with similar risk preferences ranging from risk tolerant to risk averse (Puhle, 2019). The recommended portfolios from the robo-advisors were assessed on how they performed before fees and after fees. This is because implementation costs such as robo-advisor fees can reduce the performance of the portfolios (Puhle, 2019). Furthermore, the objective was to analyse whether the recommended portfolios from the robo-advisors would perform similar to the benchmark.

¹ Ben-David *et al.* (2017) describe ETFs as securities backed up by pools that are traded on an exchange. ETFs aim to mimic the performance of the benchmark indices (Deville, 2008).

² The assumption in this study is that the robo-advisor in each country will recommend portfolios of that specific country. In the case where a different robo-advisor is used, the assumption is that the robo-advisor can recommend a portfolio with exposure to that specific country.

The second objective was to determine the exposure of the different robo-advisors to uncorrelated assets using the returns-based style analysis to provide insights into why the robo-advisors in this study gave better risk-adjusted returns than when compared to each other (Sharpe, 1992). This was done by selecting four asset classes that robo-advisors use to implement their portfolios as each robo-advisor allocates cash for asset classes differently. These four asset classes are fixed income (government bonds and corporate bonds), emerging market equity, developed market equity and real estate. These asset classes can easily be investible through an ETF and most robo-advisors use these asset classes as part of diversification within the recommended portfolio (Puhle, 2019).

1.3 Problem statement

Puhle (2019) stated that robo-advisors follow a passive investment strategy. Perold and Sharpe (1988) defined a passive investment strategy as portfolios with different asset allocations that are purchased and then held. The purpose of measuring the robo-advisors' performance was not to determine if they can outperform the benchmark but rather to analyse if the robo-advisors can deliver a performance similar to the benchmark and to provide an explanation of the performance differences between each robo-advisor and, based on asset allocation, the reason why one robo-advisor gives better risk adjusted returns than the other in this study.

1.4 Feasibility of the study

Puhle (2019) measured the performance and asset allocation of robo-advisors in Germany. Torno and Schildmann (2020) examined the performance of robo-advisors in the United States and Germany and expanded their study to include an analysis of portfolio structure and risk. There has not yet been a quantitative study on the performance of the recommended portfolios from the robo-advisors in the BRICS. However, there have been qualitative studies on robo-advisors, the performance of robo-advisors and the portfolio structure (Jacobson, 2019; Sarpong, 2020; Smith, 2020; Torno & Schildmann, 2020). Although the BRICS economies are becoming more significant in the world financial markets, no study has looked at the performance of robo-advisors in these developing economies quantitatively. This disparity emphasizes the necessity of a thorough quantitative examination of robo-advisors in the BRICS, considering their diverse financial and economic environments.

1.5 Potential benefits of the study

This study will assist investors with which robo-advisor to choose and to determine which one is most beneficial for their investment goals. This can be achieved by examining the portfolio performance of investors with similar risk preferences that range from risk tolerant to risk averse that are recommended by the different robo-advisors. The recommended portfolios can also be measured against the benchmark to establish if the portfolios perform close to the benchmark. This will help them with their wealth as choosing the wrong robo-advisor can have unfavourable results. Puhle (2019) concluded that robo-advisors with similar risk preferences still had large performance differences between them and hence finding the right robo-advisor is important. Investors also value robo-advisors and despite the market volatility caused by COVID-19, there has been an annual growth rate of 30% in the usage of robo-advisors (ITWeb, 2021).

The rest of this study is as follows: Chapter 2 provides a detailed literature review and Chapter 3 outlines the data and methodology that was used in this study. Additionally, Chapter 4 communicates the results and discussion the performance measures and the asset allocations. Furthermore, Chapter 5 will provide a conclusion for the research report.

2 Literature review

Traditional financial advice has been based on human interactions and a strong relationship between an advisor and a customer (Torno *et al.*, 2021). These services can be costly and are mostly accessible to high-net-worth individuals (Torno *et al.*, 2021). Robo-advisors assist investors through an automated process and provide portfolio recommendations based on their risk preferences and financial goals. Robo-advisors will keep track of the portfolio and rebalance it over time to cater for the needs of the investor (Sironi, 2016; Jung *et al.*, 2018). The robo-advisor process can be defined into three stages (1) Initiation and profiling, (2) Matching and customisation, and (3) Monitoring and rebalancing. In the initiation and profiling stage, customers complete a self-assessment online questionnaire on risk preference, investment goals and investment characteristics (Tertilt & Scholz, 2018). The robo-advisor creates a profile for the customer based on the answers given and will then recommend a portfolio. The robo-advisor will provide pre-selected products, which are mostly ETFs, as a basis for their recommended portfolios (Rühr *et al.*, 2019). In the matching and customisation stage, the customer's risk profile is automatically transferred to the recommended portfolio allocation. The robo-advisor will then allow the customer to customise their risk preferences related to a specific class and portfolio structure. This is done in a way that does not take away from the recommendation (Jung *et al.*, 2018). At the end of this stage, the robo-advisor will implement the chosen portfolio of the customer. In the monitoring and rebalancing stage, the customer will have access to their portfolio and will receive updates about the performance of their chosen portfolio, financial news, and educational content. The robo-advisor will then rebalance the portfolio so that it is in line with the customer's needs and risk tolerance as financial markets are ever-changing (Jung *et al.*, 2018).

2.1 Robo-advisors in Brazil

Guterman (2017) evaluated four Brazilian robo-advisors, namely Magnetis, Alkanza, Warren and Verius against legal and investment advisor best practice and provides insight into how each robo-advisor functions.

Alkanza charges 0.50% per year on equity invested (Guterman, 2017). Alkanza asks six questions such as date of birth, retirement age, investment objective, initial amount to be invested and amount to be withdrawn when retired and based on the investor's answer, a graph

of retirement savings will be shown to the investor. Alkanza allows the investor to change the variables and will rebalance the portfolio accordingly. It also does not consider risk preference due to the focus being on returns required and not risk. This means that when investors compare two stocks with the same risk, the stock with the higher return or expected return is preferred (Smith, 2020). Markowitz (1952) argued that rational investors are generally risk-averse and prefer to invest in the lowest-risk portfolio with a given expected return. Therefore, investors should consider both returns and the variance of returns when allocating capital to asset classes or securities. The asset allocation includes local and international variable income and a fixed rate fixed income. For the fixed income portfolio, indices are not purchased but a choice of private securities as there are no fixed income ETFs that can duplicate the behaviour of these indices. Investors can monitor their portfolios monthly to check the performance of the portfolios (Guterman, 2017).

Magnetis was the first robo-advisor in Brazil in 2012 and has gained 320 customers with a total of assets under management of R\$51 million (Guterman, 2017). Magnetis is an investment consultancy company that charges 0.4% per annum on the portfolio amount. In addition, it charges transaction costs and a fee for the instruments used to build a portfolio. It uses Easynvest Broker as an investment platform. It asks nine questions such as age, investment objective, investment horizon, short-term losses and loss tolerance, desired value in the future and the initial value invested and investment experience. Magnetis adopts a strategic allocation of 80% fixed income, 10% short term and 10% multimarket. The allocation concerns the risk profile more than the objective (Guterman, 2017).

Warren charges 0.8% per annum. It asks eight questions: age, investment experience, monthly income, short-term loss tolerance, reaction to short-term losses, monthly withdrawal, investment horizon, and monthly deposit. A strategic allocation is applied and only five possible portfolios are implemented through investment funds. Warren only invests in government bonds and ETFs, similar to Verius. The rebalancing and monitoring are unclear (Guterman, 2017).

Verius has an all-inclusive admin fee of 0.95%. It uses the Carretera Rico platform and asks six questions: Age, deposit amount, monthly income, reaction to short-term losses, monthly deposits and what matters most in investing. Based on the answers provided by the investor, a risk level is given to the robo-advisor. A strategic allocation is applied, and five asset classes

are included in the portfolio such as certificate of deposits, inflation, Brazilian shares, US shares and bonds. Amenc and Martellini (2002) described strategic allocation as when a portfolio allocation is based on the investor's goals and rebalances the portfolio accordingly. Verius still incorporates risky assets even when the risk level of the investor is low. This is because allocation is based on risk and not return. This means that the higher the risk tolerance of an investor, the higher the returns and when investors compare two portfolios with similar return profiles or expected returns, the stock with the lowest risk takes precedence (Smith, 2020). Allocation is done by buying government bonds and ETFs. The assumption is that equity is passively invested, and fixed income is actively invested. The robo-advisor adopts an asset management model where rebalancing and monitoring are done automatically (Guterman, 2017).

2.2 Robo-advisors in Russia

The total asset under management of the robo-advisory market in Russia in 2019 was \$72 million (Bukhanov *et al.*, 2020). The robo-advisory market in Russia is still in its beginning stages and currently, there are only 12 robo-advisory services in Russia (Bukhanov *et al.*, 2020). The robo-advisors offer automatic portfolio creation, but not all robo-advisors can manage the portfolio and rebalance it. The working method considers the risk profiling and analysis of the client's financial goals. Portfolios are created based on this information, using ETFs, bonds, and shares of Russian or foreign companies. Some of the algorithms use the Core Algorithm, created by FinEx, an ETF provider for the Moscow Exchange (MOEX). Therefore, the work of this algorithm should be studied by analysing Sberbank's "Simple Investment" service compared to the True service performed by Conomy.

The minimum investment to start using "Simple Invest" is ₹100,000 (MOEX, 2019). The commission is 1.5% of the average annual value. Before use, a questionnaire identifies the client's risk appetite, goals, and financial condition. This service uses an ETF, which is listed on MOEX (Sberbank, 2019).

Conomy's Service Right offers the following conditions: a minimum investment of ₹30,000. The commission depends on the amount managed: from ₹30,000 to ₹99,999, from ₹10,000 to ₹499,999 above ₹500,000, 1% to 3%. commission (Conomy, 2019). Before use, the client is given the option to choose the appropriate potential return and risk, according to which the

service creates a portfolio, which is managed automatically. This service creates a portfolio, using stocks and bonds, and ETFs are excluded (Conomy, 2019). Traditional financial services cost ₦3,000-7,000 for one treatment, ₦40,000-100,000 for financial planning and 10% to 20% profit for portfolio management. According to statistics, in 2019, the assets under the management of robo-advisors increased by 106%, and the number of users also increased by 95% and is estimated at 8 100 people (Statista, 2019).

2.3 Robo-advisors in India

Robo-advisors in India have grown in recent years and continue to grow rapidly (Bhattacharyya & Bhattacharyya, 2020). The assets under management for robo-advisors in India are expected to grow at a compound annual growth rate (2022-2027) of 24%, totalling \$46 billion by 2027 (Statista, 2022a). However, there is still plenty of room for growth as the robo-advisory is still in its infancy stage. The Indian Robo-Advisory market can be classified into three broad categories: Fund-based Robo-Advisory, Equity-based Robo-Advisory and Comprehensive wealth consulting.

Bhattacharyya and Bhattacharyya (2020) highlight the differences between all three categories:

Fund-based robo-advisors focus on risk profiles and goal-based recommendations for their clients. Investments of single asset class funds can be managed or traded on an exchange. These investments are suitable for new and seasoned investors who are relatively risk averse and want to limit direct exposure to stocks. Almost none of them charge clients for service, and the revenue comes mainly from fund distribution fees. The financial situation assessment, human monitoring and advisory elements are still very limited (Bhattacharyya & Bhattacharyya, 2020).

Stock advisors focus only on stock portfolios. These solutions allow execution through multiple brokers. These portfolios are suitable for investors with a good understanding of the stock market and have a moderate to strong risk profile but prefer expert advice to design the most optimal portfolio. Some of the robo-advisors offer themed portfolios designed around specific areas or investment philosophies. The prices are usually fixed, which can be an annual fee or a transaction fee and do not provide financial assessment, people consulting and financial planning services (Bhattacharyya & Bhattacharyya, 2020).

A comprehensive wealth management solution focuses on aggregating a client's net financial value, understanding their risk appetite, and then providing comprehensive wealth management services at the individual or family level. In addition to fund-based portfolio recommendations, they also offer exclusive financial planning, portfolio management, and human financial advice on estate and estate planning. The pricing is based on fees for a combination of services (Bhattacharyya & Bhattacharyya, 2020).

2.4 Robo-advisors in China

Compared with developed countries such as the United States, China's robo-advisory platform started relatively late, and the development of the entire industry and platform is still in the beginning stages (Huang, 2021). In 2015, several emerging robo-advisory consulting platforms were officially launched in China and with the low cost and ability to spread risk, robo-advisors can meet the financial needs of the public (Zheng *et al.*, 2018).

Unlike their Western counterparts, who can make investment decisions on behalf of their clients, robo-advisors in China tend to be more limited. The robo-advisors often provide portfolio recommendations, but the final investment decision must be made by the user due to regulatory restrictions (Goh & Osio, 2020). However, the pilot implementation of China's mutual fund advisor program in October 2019 could alleviate this limitation. The program will allow asset managers and fund distributors to provide personalised investment advice and maintain discretionary control over a client's portfolio. As a result, the robo-advisor will be allowed to automatically execute trades without client consent each time, providing a more seamless user experience (Goh & Osio, 2020).

Chinese robo-advisors can be classified into three models: the classical model, asset allocation advisory model and stock-specific recommendation model (Guo, 2020). The classical model is one where robo-advisors must work together with foreign companies to provide management functionality. The asset allocation advisory model focuses on open-ended mutual funds but does not provide automated account management services to clients. Finally, the stock-specific recommendation model focuses on stock investments but does not provide automated account management services to clients (Guo, 2020). Furthermore, based on the business model, China's robo-advisory platforms can be divided into three categories: robo-advisory platforms

based on traditional financial firms, such as Capricorn Intelligent Investment, affiliated with Merchants Bank of China. Secondly, there are robo-advisor platforms that are based on internet finance companies or wealth management companies, such as Tonghuashun IFind Intelligent Investment Consultants and lastly, Independent robo-advisor platforms, such as Money Manager's Rubik's Cube (Gao, 2018).

2.5 Robo-advisors in South Africa

Compared to the United States and the United Kingdom, the robo-advisory market in South Africa is still emerging and currently, most of it is being provided by banks (Jacobson, 2019). This is primarily because few financial service providers have a large enough customer base and investment portfolios to achieve the economies of scale needed to justify implementing automated robo-advisors (Smith, 2020). The robo-advisory platforms that currently exist are the Nedgroup Investment Advisor's Eva, Sanlam Smart Invest, OUTvest, Sygnia robo-advisor and Bizbank (which is financed by Anchor Capital) (Sarpong, 2020). Sanlam's Smart Invest starts by asking the reason for investing and offers five options to choose from: Education, My Future Self, Just Invest, Dream Home, and Something Special. Among other steps, Smart Invest provides 18 questions for the investor to determine their risk profile and then the investor will have investment options to choose from. Eva from Nedgroup Investment as well as OUTvest has a responsive approach and can make recommendations in less than 10 minutes (Sarpong, 2020). These firms develop their robo-advisors and create web-based platforms that will attract investors and savers in South Africa (Smith, 2020). Assets under management are expected to grow at a compound annual growth rate (2022-2027) of 22% totalling \$18 billion by 2027 (Statista, 2022b).

2.6 Asset allocation

Sharpe (1992) defines asset allocation as the allocation of an investor's portfolio among broad asset classes such as stocks, bonds, and cash. Once a set of asset classes has been identified, it is important to determine the exposure of each component of an investor's overall portfolio to variations in their returns. This information may be aggregated to determine the effective composite of an investor's assets. If it does not match the desired blend, appropriate modifications can be made. The main factor that determines the allocation of the customers' financial resources is the time horizon and risk tolerance to achieve the expected returns. It is important to do this because it helps identify the risk and returns of specific investments

together with their correlation. Based on this, a diversified portfolio is built to match the customer's needs to reduce risk and achieve returns (Cappello & Ruffoni, 2018). Asset class diversification occurs when different asset classes form part of a portfolio and improve the returns of the portfolio, which is a benefit of diversification in asset allocation when using different asset classes (Ibbotson & Kaplan, 2000). By investing in two assets with negative correlations, if one asset has poor returns, the investor can counteract the losses with the positive returns from the other asset (US Securities & Exchange Commission, 2010). In terms of asset classes, all robo-advisors cover stocks such as domestic and international and bonds such as fixed income, corporate and government ones. Few robo-advisors cover only stocks and bonds. Some cover real estate in the form of Real Estate Investment Trusts, cash and money market instruments and commodities and natural resources (Cappello & Ruffoni, 2018). Most of the time, robo-advisors invest in ETFs which are a passive strategy which tracks market benchmarks to represent each asset class (Cappello & Ruffoni, 2018).

Most robo-advisor algorithms are formed on Modern Portfolio Theory (MPT) to create and manage portfolios by optimising asset allocation across various asset classes such as equities and bonds (Bjerknes & Vukovic, 2017). Similarly, Beketov *et al.* (2018) analysed 219 robo-advisors worldwide and found that most robo-advisors use MPT as a framework. MPT is based on Markowitz (1952) and is one of the most popular models of asset allocation. MPT states that an optimal portfolio is achieved when expected returns are maximised given a risk level tolerance. Robo-advisors build portfolios with higher risk by expanding the ratio of equity to bonds (Abraham *et al.*, 2019). The portfolio is adjusted by considering investment objectives and risk tolerance (Abraham *et al.*, 2019). The algorithms are also designed to constantly monitor and rebalance the portfolio whenever there are market changes or the investment goals or risk tolerance of the investor changes. Additionally, the result of the modern portfolio theory is diversification. To achieve this at a low cost, the robo-advisor offers ETFs and index funds. ETFs and index funds are similar, but the main difference is that ETFs are traded on an exchange throughout the day while index funds can only be traded at the end of the day (Narend, 2014). In practice, robo-advisors tend to follow a more careful approach and offer funds on a broad spectrum that have a long operating history, market liquidity, and good performance over time (Phoon & Koh, 2018).

Classical models such as MPT, proposed by Harry Markowitz, provide a theoretical framework for asset allocation. MPT proposes constructing portfolios along the efficient frontier, which

represents the optimal trade-off between risk and return (Markowitz, 1952). However, current models have been criticised for relying on historical data and simplifying assumptions and the argument is that traditional asset allocation models may not adequately capture the complexity of real markets. There are challenges such as assumptions of rationality, sensitivity to input parameters, and inability to account for changes in market conditions. Furthermore, traditional models may fail to address investor behavioural biases and abnormal return distributions (Fama & French, 2004).

Alternative approaches to asset allocation attempt to address the limitations of traditional models. These include factor-based models such as the Fama-French three-factor model (Fama & French, 1993) and risk parity strategies (Chaves *et al.*, 2012), which allocate capital based on risk contribution rather than market capitalisation. Empirical studies play a crucial role in evaluating asset allocation strategies. Researchers use a variety of testing methods, including historical back testing, Monte Carlo simulations, and out-of-sample validation. These studies evaluate the performance of different asset allocation strategies under different market conditions and assess their robustness over time (Campbell & Viceira, 2002).

The Monte Carlo simulation is a powerful asset allocation testing tool that allows researchers to simulate thousands of future scenarios based on historical data. This approach provides insight into the range of potential outcomes and helps assess the robustness of asset allocation strategies under different market conditions (Glasserman, 2003). The out-of-sample testing involves evaluating asset allocation strategies based on data not used for development, thereby providing a more rigorous assessment of performance. Studies by Campbell and Viceira (2002) emphasize the importance of out-of-sample validation to ensure the generalisability and effectiveness of asset allocation models.

Bootstrapping and resampling methods involve repeatedly sampling historical data to generate simulated data sets. These techniques allow researchers to evaluate the stability and reliability of asset allocation strategies, especially in scenarios with limited data or nonnormal return distributions (Efron & Tibshirani, 1994). The Bayesian approaches provide a flexible framework for testing asset allocation, integrating prior beliefs, data, and model parameters to estimate the posterior distributions of portfolio returns. The study by Andrei and Hsu (2020) demonstrates the usefulness of Bayesian methods in asset allocation tests and highlights their advantages in managing uncertainty and incorporating expert judgment.

Recent advances in machine learning and artificial intelligence have allowed researchers to develop sophisticated asset allocation models that can adapt to changing market conditions and identify non-linear patterns in data. The studies of Gu *et al.* (2020) and Lopez de Prado (2018) demonstrate the potential of machine learning techniques to improve asset allocation testing.

Behavioural finance insights highlight the importance of understanding investor behaviour when considering asset allocation. Biases such as loss aversion, overconfidence, and herd behaviour can influence investment decisions and affect portfolio performance. Incorporating behavioural factors into asset allocation models increases predictive power and improves decision making (Barberis & Thaler, 2003). Dynamic asset allocation strategies adjust portfolio allocations in response to changing market conditions, economic indicators, or valuation criteria. Tactical asset allocation involves actively changing allocations to take advantage of short-term market inefficiencies. Research on dynamic and tactical asset allocation evaluates their ability to improve returns and manage risk compared to static allocation strategies (Ang & Bekaert, 2007).

The rise of robo-advisors and algorithmic asset allocation platforms has democratised access to advanced portfolio management tools. These platforms use algorithms to automate asset allocation decisions based on predefined investment objectives and risk appetite. Research on robo-advisors evaluates their performance, cost-effectiveness, and suitability for different investor profiles (Dolginow *et al.*, 2017).

Asset allocation is critical in determining a portfolio's risk-return profile, as demonstrated by several foundational studies in finance (Brinson *et al.*, 1986). However, to fully understand the effectiveness of these allocation strategies, their outcomes must be evaluated using performance measures. As a result, the following section examines the literature on performance metrics, emphasizing how they are used to evaluate the success of various asset allocation approaches.

2.7 Performance measures

A portfolio performance measure is used to determine how a particular investment portfolio has performed relative to comparative benchmarks. Methods of assessing performance usually

fall into two categories: conventional methods such as benchmark comparison and style comparison and risk-adjusted methods such as Sharpe ratio, Treynor ratio, Jensen's alpha, and Treynor squared (Verma & Hirpara, 2016). The authors also explored the Sharpe ratio's limitations and found that the Sharpe ratio is still used in practice as a performance measure. Its main advantage is that it can be calculated directly from the set of observed returns without requiring additional information about the source of the returns and is systematic and rational. Most traditional performance measures, such as the Sharpe ratio, assume that the returned distribution is either normal or log normal as they are based on the theory of mean-variance. A higher Sharpe ratio indicates better performance of the fund (Srivastava & Mazhar, 2018).

The Treynor ratio offers another risk or reward ratio and calculates the risk premium per unit of systematic risk (Treynor, 1969). The difference between the Sharpe ratio and the Treynor ratio is that the systematic risk of the portfolio is used as the risk parameter and cannot be eliminated by diversification (Verma & Hirpara, 2016). It is measured by a parameter known as "beta". The Sharpe ratio measures the portfolio risk premium and the portfolio risk or standard deviation thereof, while the Treynor ratio compares the portfolio risk premium and the portfolio systematic risk to the beta measure (Verma & Hirpara, 2016). A higher Treynor ratio indicates a higher excess return per unit of systemic risk, as measured by the beta coefficient (Jakšić *et al.*, 2015).

Another way to measure portfolio performance is Jensen's alpha. Jensen's alpha was developed by Jensen (1968) and is based on the Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965), and Mossin (1966). Alpha represents the amount by which the portfolio's average return differs from the CAPM's expected return. Alpha is determined by the fundamentals of the companies in the portfolio, as opposed to beta, which measures portfolio returns based on volatility. Alpha may be greater than, less than, or equal to zero. An alpha greater than zero indicates that the portfolio has achieved a return above the portfolio's expected return (Verma & Hirpara, 2016).

Although these are the most common measures of academic performance, they also have some drawbacks. If the portfolio is well diversified, all three performance measures, Sharpe, Treynor and Jensen's Alpha, will give the same performance (Verma & Hirpara, 2016). The Sharpe ratio is most appropriate when the portfolio is not well diversified, or when the portfolio represents an investor's total assets, as the standard deviation of the portfolio's returns is the

appropriate measure of risk. This caters for the portfolios recommended by the robo-advisor that are not well diversified. However, if the portfolio is well diversified, some of the overall risks are diversified and systematic risk³ is the most appropriate risk indicator. Both the Treynor ratio and Jensen's alpha can be used to assess the performance of well-diversified portfolios of securities. This is to cater for well-diversified portfolios. These two ratios are also suitable if the portfolio represents only a sub-portfolio or part of the client's portfolio. Both Sharpe and Treynor ratios can be based on either ex-ante or ex-post excess returns and standard deviations (Sharpe, 1992).

However, recent research suggests that traditional performance measures can be manipulated by fund managers (Weisman, 2002; Goetzmann *et al.*, 2007; Brown *et al.*, 2010). Goetzmann *et al.* (2007) have shown that single-valued performance measures are prone to manipulation to improve performance scores without additional information by changing the future distribution of returns. The authors demonstrated that these measures could be improved by varying leverage or market exposure. Fund managers can improve the portfolio's performance scores by reducing the exposure to the market in the next period. Fund managers can improve the portfolio's performance by increasing the portfolios' exposure to the market after experiencing poor results (Brown *et al.*, 2010). Reported return smoothing, which is the most common technique for using these measures, can also improve performance scores because it skews risk measures such as return volatility (Brown *et al.*, 2010).

As an antidote to these activities, Goetzmann *et al.* (2007) formed a manipulation-proof performance measure (MPPM). The authors tested seven performance measures which are the Sharpe ratio, Jensen's alpha, Treynor ratio, Appraisal ratio, generalised alpha, Sortino and Van der Meer ratio (1991), Sortino, Van der Meer, Plantinga ratio (1999), and the three regression intercepts which are the CAPM alpha, Treynor and Mazuy (1966) and Henriksson and Merton (1981) and found that all these performance measures are subject to manipulation. Goetzmann *et al.* (2007) stated that manipulation-proof performance measure can be defined by these three characteristics: (1) The value of the score should not depend on the monetary value of the portfolio; (2) Unskilled investors cannot hope to improve their estimated score by deviating from a benchmark portfolio and at the same time, sophisticated investors will be able to create

³ Systematic (market) risk cannot be eliminated by diversification and unsystematic (specific) risk can be reduced through proper diversification.

more appreciated portfolios and still be able to do so by taking advantage of arbitrage opportunities; (3) The measure must be consistent with the standard equilibrium conditions of the financial market.

The reliability of most performance measures, including the Sharpe ratio, assumes that reported returns are independent and equally distributed. However, the Sharpe ratio cannot statistically satisfy the above assumptions (Yu, 2011). Goetzmann *et al.* (2007) showed in their study that the rate of Sharpe being intentionally manipulated would result in a ratio that is 18% higher than the normal rate and that the alpha is similarly manipulated because there is a positive relationship between the alpha and the Sharpe ratio. Other manipulation methods, such as smoothing returns over several intervals, are also used. Bollen and Pool (2008) examined the independence of profits and found that managers' report profits, but delay reporting losses. Deliberately lowering the volatility of fund returns inevitably increases the risk-to-risk ratio, including the Sharpe ratio (Yu, 2011). In another study, Bollen and Pool (2009) again found evidence to support the above hypothesis that for hedge fund returns, the number of small gains far outweighs the number of small losses. The authors argued that these losses stem from profits that are temporarily overvalued due to the deferral of fee payments. If fund managers do not manipulate the value of their performance, then the MPPM should be consistent with other current metrics because the MPPM also increases with performance (Brown *et al.*, 2010). However, if the performance ratios of other measurements are manipulated, the MPPM scores will differ significantly from these. Therefore, if MPPM is not performance-manipulated but other current metrics are manipulative, then the rank correlation between the current metrics will be very high (Brown *et al.*, 2010). Since some robo-advisory firms or robo-advisors still use financial advisors as part of the process, the MPPM will give an indication if the performance scores have been manipulated.

In summary, robo-advisors comprise an automated process that is used to provide recommendation portfolios, mostly ETFs, on a questionnaire. There are three process such as initiation and profiling, matching and customisation and lastly monitoring and rebalancing. Guterman (2017) examined four robo-advisors, namely Magnetis, Alkanza, Warren and Verius and further provided details on how each robo-advisor functions. Robo-advisors in India have experienced exponential growth and the Indian market can be divided into three categories such as Fund-based robo-advisor, Equity-based robo-advisor and Comprehensive wealth consulting. The robo-advisors in China had a relatively late start compared to its counterparty

and began in 2015. The robo-advisors can be classified into three categories, traditional financial firms, wealth management companies and independent robo-advisor platforms. Robo-advisors in Russia are still in the beginning stages with only 12 robo-advisors as of 2020. Robo-advisors in South Africa are still developing and mostly provided internally by banks. Since robo-advisors recommend portfolios, it is important that asset allocation is considered as some robo-advisors do not only invest in equity and bonds but also commodities, money market instruments and natural resources. Performance measures such as Sharpe ratio, Treynor ratio and Jensen's alpha are used to determine the performance of the portfolios. However, these performance measures are subject to manipulation. The MPPM will provide an indication of whether the performance results have been manipulated.

3 Description of data and research methodology

3.1 Data

The data for this study consisted of four robo-advisors with one robo-advisor from each country. This included a total of 62 recommended portfolios. Additionally, the monthly portfolios return was included and covered a period from 2015 to 2022. Furthermore, the data was collected from Bloomberg and Iress. Most independent robo-advisors in BRICS countries have only become available since 2015 (Zheng *et al.*, 2018; Sun, 2021). The specific robo-advisors were chosen because there are robo-advisors that have portfolios that are not publicly available or are integrated within the banks which makes it difficult to access the recommended portfolios. Each recommended portfolio was measured against the benchmark relevant to the country of origin. The recommended portfolios also included investors with similar risk preferences ranging from risk tolerant to risk averse. Each portfolio recommended has a portfolio summary that states the risk profile of the portfolio which can help determine the risk tolerance of an investor as the assumption is that an investor with a high risk tolerance will choose a portfolio that has a high risk profile (see **Appendix C** for BRICS characteristics).

3.2 Research methodology

3.2.1 Sharpe ratio

The Sharpe ratio measures the excess return earned per unit of total risk (Sharpe, 1964). The formula is as follows:

$$SR_i = \frac{\mu_i - r_f}{\sigma_i} \quad (1)$$

For the robo advisor, μ_i is the sample mean monthly return on the recommended portfolio, r_f is the risk-free rate and σ_i is the standard deviation of the monthly return for the robo-advisor (Puhle, 2019). The Sharpe ratio was reported on the recommended portfolios and the benchmarks.

3.2.2 Jensen's alpha

Jensen's alpha measures the risk-adjusted return of a portfolio related to the expected market return from the CAPM (Jensen, 1968). The formula is as follows:

$$r_{it} = \alpha_i + \beta_i r_M + \varepsilon_i \quad (2)$$

where r_{it} is equal to the excess monthly return on the recommended portfolio, r_M is equal to the monthly excess return of the market. Each country had a benchmark used as a proxy. Jensen's alpha was reported on the recommended portfolios and the benchmarks.

3.2.3 Treynor ratio

The Treynor ratio measures the risk premium per unit of systematic risk (Treynor, 1969).

$$TR = \frac{r_{p,t} - r_{f,t}}{\beta_p} \quad (3)$$

where $r_{p,t}$ is the monthly return on the robo advisor, $r_{f,t}$ is the risk-free rate and β_p is the beta of the portfolio. The Treynor ratio was reported on the recommended portfolios and the benchmarks.

3.2.4 Manipulation-proof performance measure

The manipulation-proof performance measure (MPPM) can be defined as the degree of certainty equivalent to the annual geometric excess return of a particular fund (Brown *et al.*, 2010). The equation is as follows:

$$\theta = \frac{1}{(1-\rho)\Delta t} \ln \left(\frac{\frac{1}{T} (\sum_{t=1}^T [(1+r_t)])}{[1+r_f]^{1-\rho}} \right) \quad (4)$$

Where

$$p = \frac{\ln [E(1+r_{benchmark})] - \ln (1+r_{benchmark})}{Var(\ln (1+r_{benchmark}))} \quad (5)$$

r_t is the monthly return on the portfolio recommended by the robo-advisor at time t . The r_f is the risk-free rate. (See Error! Reference source not found. for the risk-free rates). T is equal to the total number of observations and Δt is the total length of time between observations. The ρ measures the risk-averse coefficient measure of the market. The $r_{benchmark}$ is the monthly return on each country's benchmark.

3.2.5 Asset allocation

To show the exposure to different asset classes, an analysis was completed on each robo advisor's return series using common asset across all portfolios (Puhle, 2019). Four common asset classes were chosen such as government and corporate bonds, developed and emerging

market equity and real estate. Puhle (2019) used a style analysis to capture the exposure of each robo-advisor to mutually exclusive asset classes. A constrained regression was run using the following model:

$$r_{it} = \sum_{j=1}^r \beta_j R_j + \varepsilon_i \quad (6)$$

r_{it} is equal to the monthly return for robo advisors.

R_j is equal to the monthly return on the asset class.

$\sum_{j=1}^r \beta_j = 1$ and $\beta_j \geq 0 \forall j = 1, \dots, 5$.

To compare the different styles between the robo advisors, a common style was calculated. The formula for common style is as follows:

$$CS_{ij} = \sum_{a=1}^5 \min\{\beta_{i,a}, \beta_{j,a}\} \quad (7)$$

The $\beta_{i,a}$ represents the exposure of the robo-advisor i to the asset class a .

3.3 Limitations

The researcher was aware that there could have been a challenge with the collection of data for internal robo-advisors - robo-advisors that are internally generated by companies (Jacobson, 2019; Sarpong, 2020; Smith, 2020). It may have been necessary to substitute those specific robo-advisors with robo-advisors that are not internally generated by companies which could potentially have affected the results as they originate in developed markets and can also recommend portfolios in one of the BRICS countries. These portfolios can be slightly different from the portfolios that internally generated robo advisors recommend.

4 Results

In this study, the performance of the recommended portfolios from the different robo-advisors was measured using the Sharpe ratio, Treynor ratio, Jensen's alpha and the manipulation-proof performance measure. The performance measures were also used to determine how the recommended portfolios perform before and after fees are considered. Furthermore, the performance measures were used to determine if the portfolios perform similar to the benchmark. The results section provides the outcomes of the performance measures of the portfolios from the BRICS countries.

4.1 Brazil

Magnetis was the chosen robo-advisor for Brazil and has a product range of only ETFs. To use the robo advisor, the user needs to download the app and complete the questionnaire and then a portfolio is compiled on the user's behalf. Alternatively, the user can reach out to a consultant. The monitoring of the portfolios can be seen via the app. The management fee is 0.50% per year on the value of the portfolio regardless of the segment and is charged proportionally monthly. A 15% performance fee is charged in January and July of each year on any portfolio that outperforms the benchmark. There are different amounts that lead to different access within the robo advisor. R\$1 million provides access to Infinity, which is an exclusive segment. R\$100 000 provides access to a private consultant and R\$1 000 provides the user access to the diversification strategy (Magnetis, n.d.)

Out of the 45 portfolios on Magnetis, eight portfolios were selected as these eight portfolios met the period criteria of 2015 to 2022 together with the respective benchmark and the portfolio data was not publicly available. Out of the eight portfolios, three portfolios are for risk averse investors, two are for moderate investors and three are for risk tolerant investors.

4.1.1 Sharpe ratio

The Sharpe ratio was used as performance measure for each of the recommended portfolios. It considers the total risk of the portfolio and does not account for systematic risk and was calculated for investors with high to low risk tolerance.

Figure 1 presents the summary of the performance outcomes of the Sharpe ratio for investors with high risk tolerance, both before and after accounting for fees. Between 2015 and 2022, the portfolios generally underperformed relative to the benchmark. However, in 2020, the *Composite Ações FI Ações* and *CFO Infraestrutura Tura I FIP Multiestratégia* slightly exceeded the benchmark. In 2021, no performance disparities emerged between the portfolios and the benchmark, with the portfolios exhibiting divergent performance. Despite these variations, the portfolios' overall performance remained largely in line with the benchmark. After fees were considered, the reduction in portfolio performance was not significant.

Figure 1

Summary of Sharpe ratio for high risk tolerance investors before and after fees

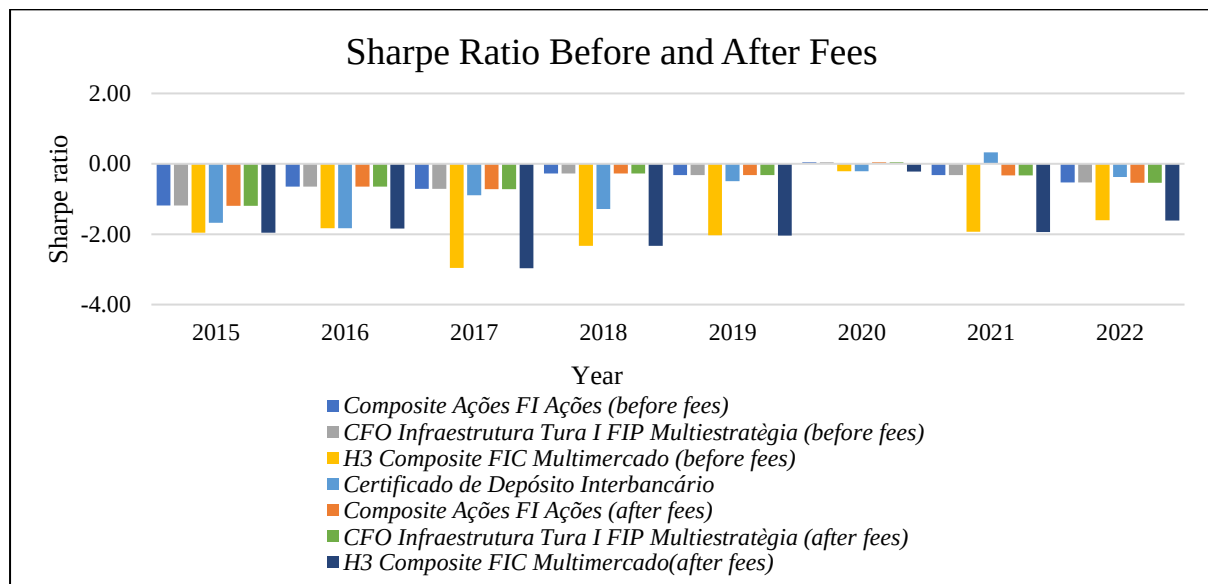


Figure 2 illustrates the Sharpe ratio results for investors with moderate risk tolerance, both before and after the consideration of fees. From 2015 to 2022, all portfolios underperformed relative to the benchmark. In 2021, the portfolios exhibited performance that diverged from the benchmark. However, over the entire period, the portfolios' overall performance remained generally comparable to that of the benchmark. The reduction in performance after accounting for fees was not significant.

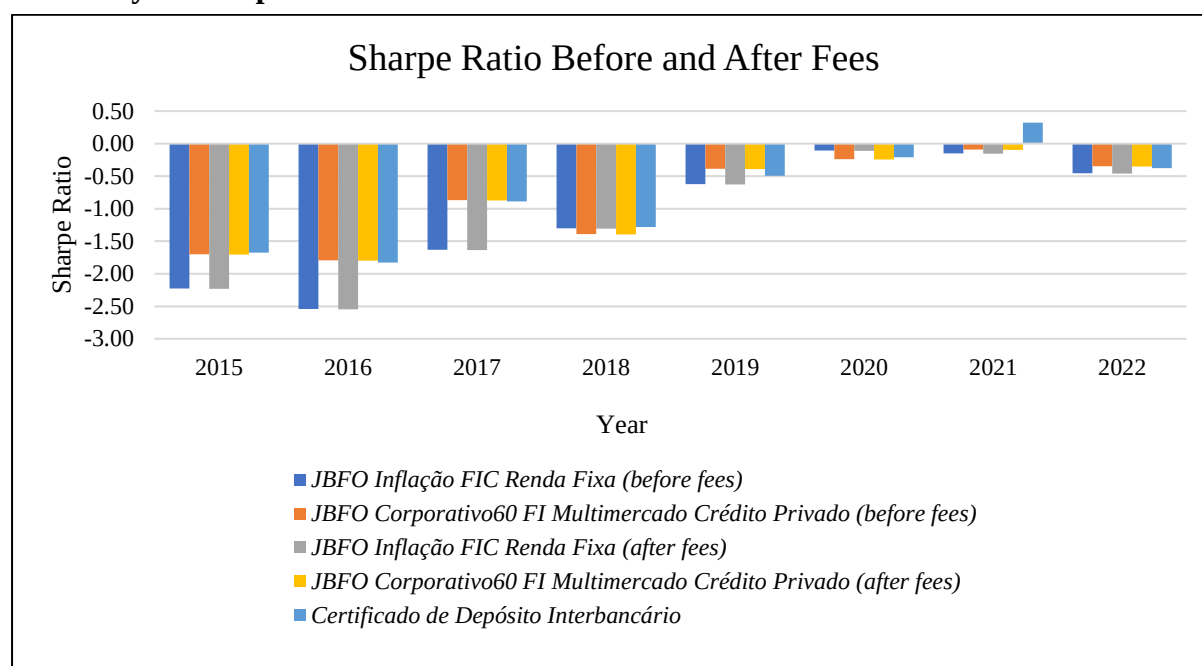
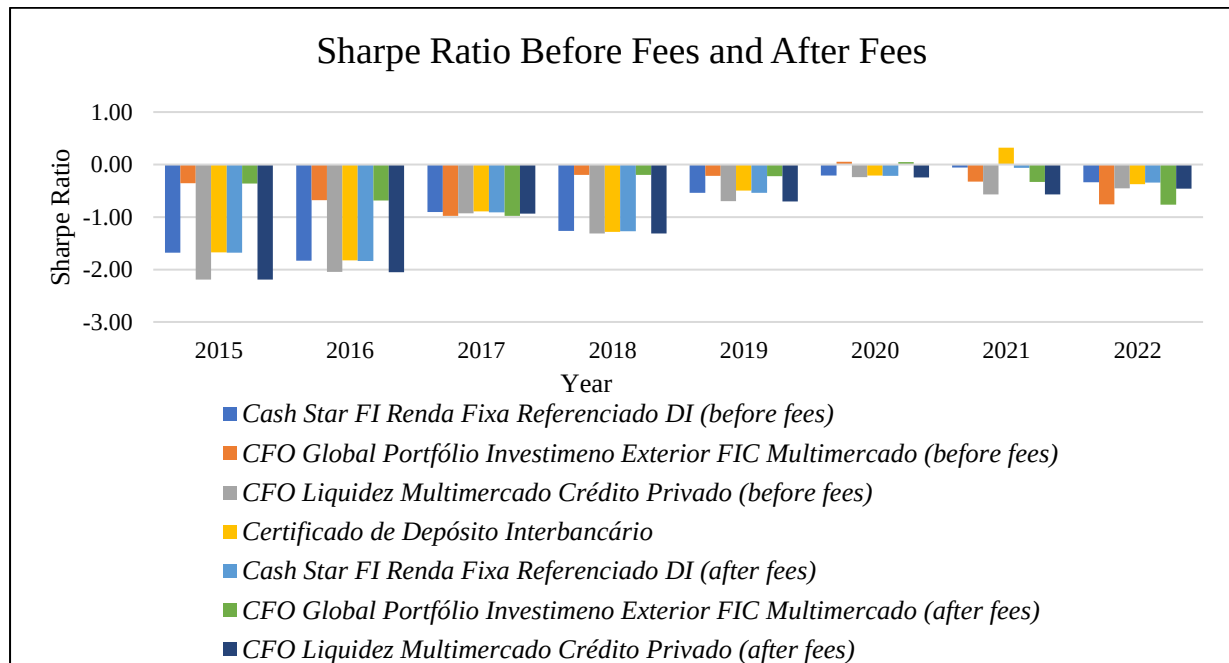
Figure 2**Summary of Sharpe ratio for moderate risk tolerance investors before and after fees**

Figure 3 presents the Sharpe ratio results for investors with low risk tolerance, both before and after accounting for fees. From 2015 to 2022, the portfolios generally underperformed the benchmark, except for the *CFO Global Portfólio Investimento Exterior FIC Multimercado*, which slightly outperformed the benchmark in 2020. Overall, the portfolios' performance was largely in line with the benchmark, except in 2021, when they diverged. Despite this deviation, the portfolios otherwise remained comparable to the benchmark. The reduction in performance after factoring in fees was insignificant.

Figure 3**Summary of Sharpe ratio for low risk tolerance investors before and after fees**

4.1.2 Treynor ratio

The Treynor ratio measures the excess return of each portfolio relative to its systematic risk.

Figure 4 presents the Treynor ratio results for investors with high risk tolerance, both before and after fees. The years 2015, 2020, and 2022 reported negative Treynor ratios. The *Composite Ações FI Ações* and *CFO Infraestrutura Tura I FIP Multiestratégia* slightly outperformed the benchmark in 2016, 2017, and 2019. Additionally, the *H3 Composite FIC Multimercado* demonstrated slight outperformance relative to the benchmark from 2016 to 2019. However, in 2021, the portfolios diverged from the benchmark's performance. After accounting for fees, the reduction in portfolio performance was minimal.

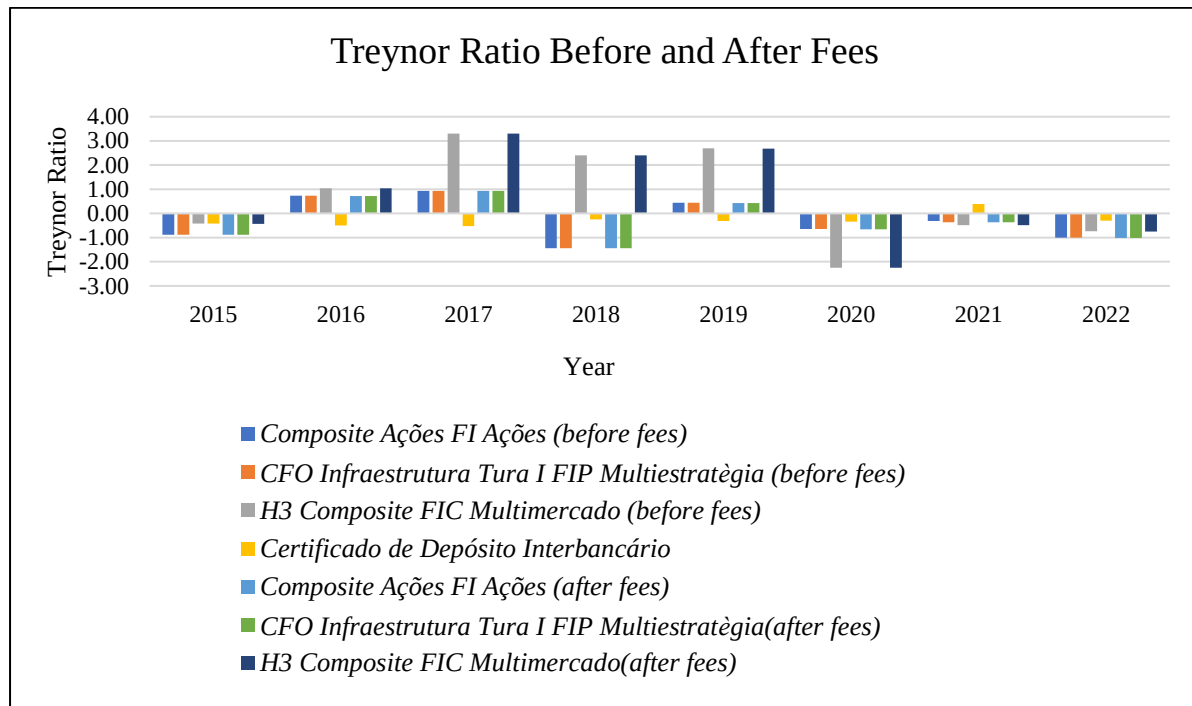
Figure 4**Summary of Treynor ratio for high risk tolerance investors before and after fees**

Figure 5 presents the Treynor ratio results for investors with moderate risk tolerance, both before and after accounting for fees. The Treynor ratio was negative for all portfolios in 2018 and 2022. The *JBFO Inflação FIC Renda Fixa* slightly outperformed the benchmark in the years 2015 through 2017 and 2019 through 2021. Similarly, the *JBFO Corporativo60 FI Multimercado Crédito Privado* showed slight outperformance relative to the benchmark in 2015, 2017, and 2019 through 2020. In 2021, the portfolios did not align with the benchmark performance. Prior to the consideration of fees, the portfolios' performance was comparable to the benchmark, and the reduction in performance after accounting for fees was insignificant.

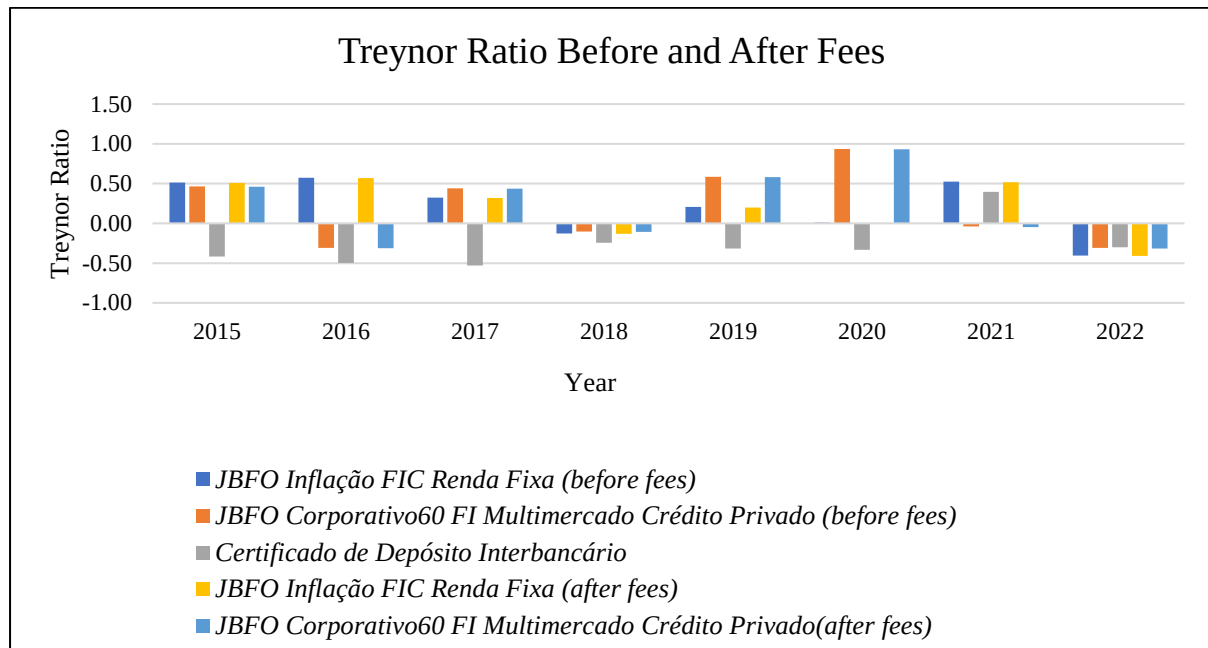
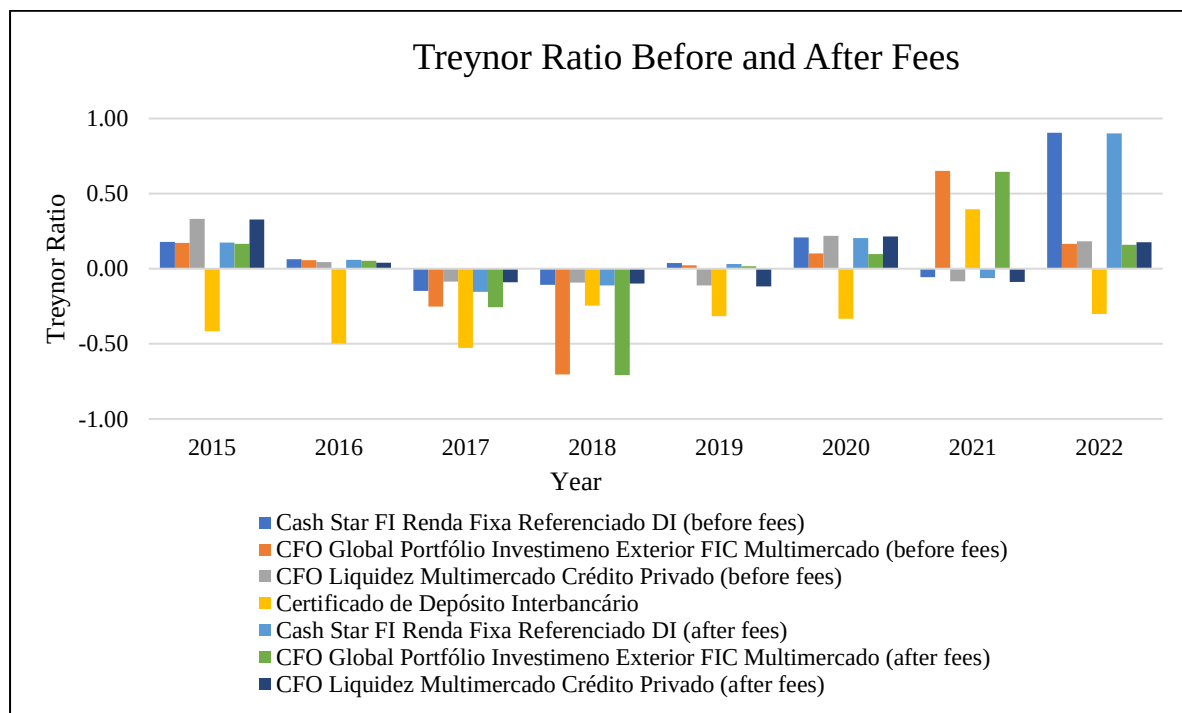
Figure 5**Summary of Treynor ratio for moderate risk tolerance investors before and after fees**

Figure 6 illustrates the Treynor ratio results for investors with low risk tolerance, both before and after accounting for fees. There was a positive Treynor ratios for all portfolios in the years 2015, 2016, 2020, and 2022. Additionally, the portfolios exhibited slight outperformance relative to the benchmark in 2017 and 2018. However, in 2017, 2019, and 2020, the *CFO Liquidez Multimercado Crédito Privado* did not align with the benchmark performance. Conversely, the *CFO Global Portfólio Investimento Exterior FIC Multimercado* slightly outperformed the benchmark in 2021. Overall, the portfolios' performance was generally consistent with the benchmark, and the impact of fees on portfolio performance was minimal.

Figure 6**Summary of Treynor ratio for low risk tolerance investors before and after fees**

4.1.3 Jensen's alpha

The Jensen's Alpha measures the risk-adjusted returns of a portfolio relative to the market. **Figure 7** presents the Jensen's alpha results for investors with high risk tolerance, both before and after accounting for fees. The results indicate that Jensen's alpha was negative for all portfolios, both before and after fees, signalling slight underperformance relative to the market.

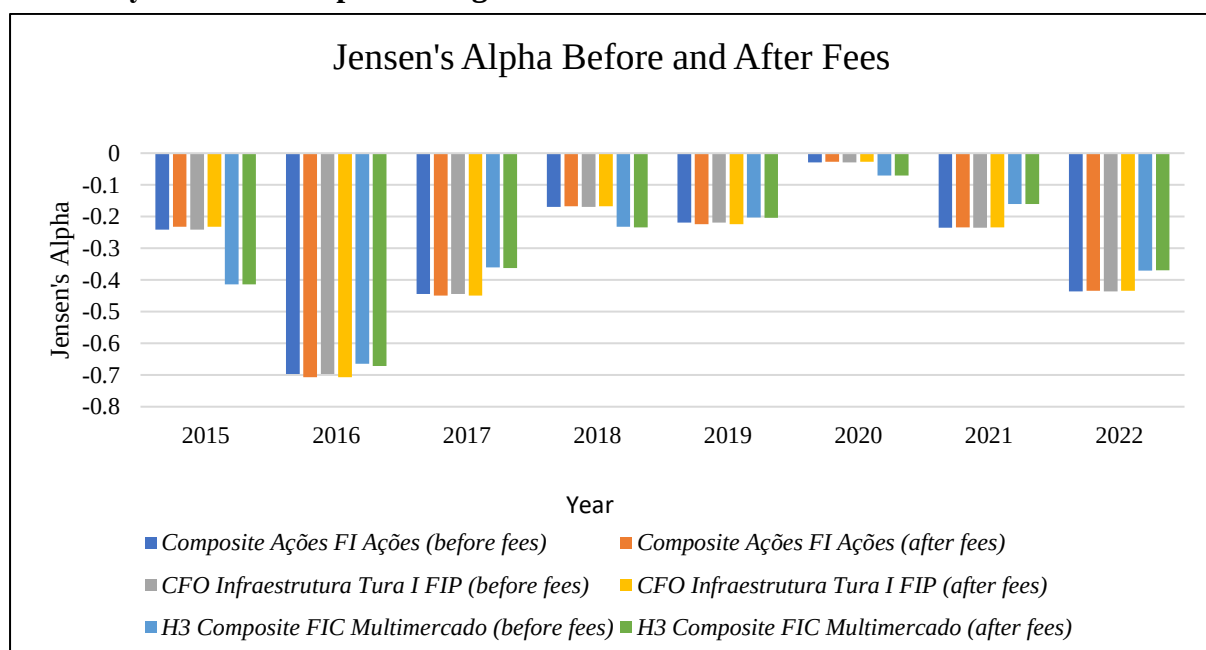
Figure 7**Summary of Jensen's alpha for high risk tolerance investors before and after fees**

Figure 8 presents the Jensen's alpha results for investors with moderate risk tolerance, both before and after accounting for fees. The findings indicate that Jensen's alpha was negative for all portfolios, reflecting underperformance relative to the market both before and after the consideration of fees.

Figure 8

Summary of Jensen's alpha for moderate risk tolerance investors before and after fees

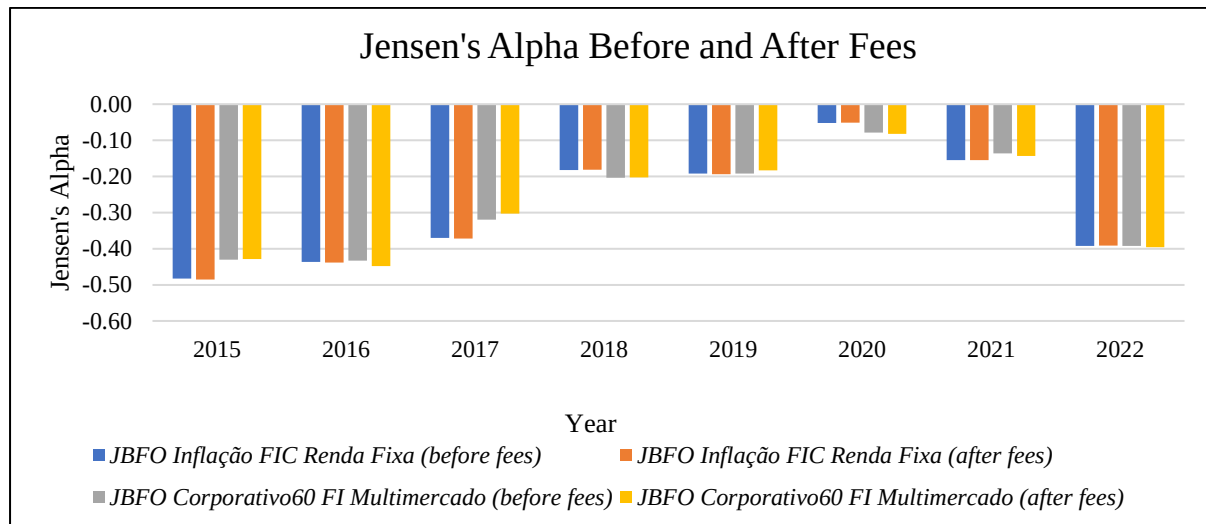
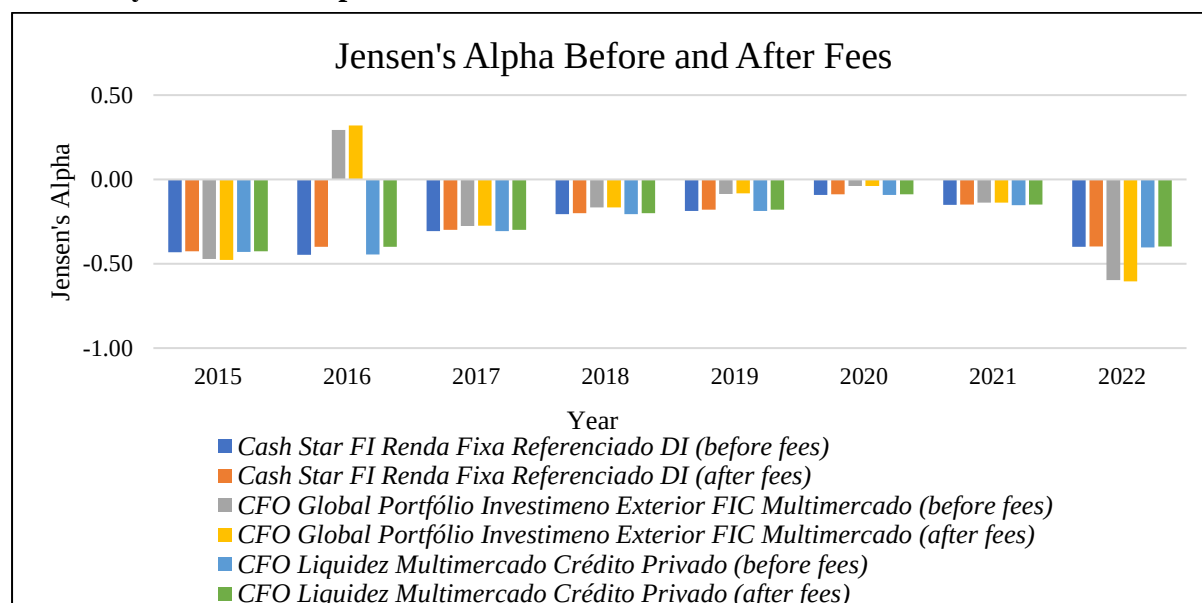


Figure 9 presents the Jensen's alpha results for investors with low risk tolerance, both before and after accounting for fees. The results indicate that Jensen's alpha was negative for all portfolios, reflecting underperformance relative to the benchmark. However, the *CFO Global Portfólio Investimento Exterior FIC Multimercado* slightly outperformed the benchmark in 2016.

Figure 9**Summary of Jensen's alpha for low risk tolerance investors before and after fees**

4.1.4 Manipulation-proof performance measure

The manipulation-proof performance measure (MPPM) assesses whether traditional performance metrics are susceptible to manipulation and whether their results can be easily altered. **Figure 10** presents the MPPM results for investors with high risk tolerance, both before and after fees were considered. The findings show that the MPPM was positive for all portfolios, both before and after fees, with minimal differences observed between before and after fees.

Figure 10

Summary of manipulation-proof performance for high risk tolerance investors before and after fees

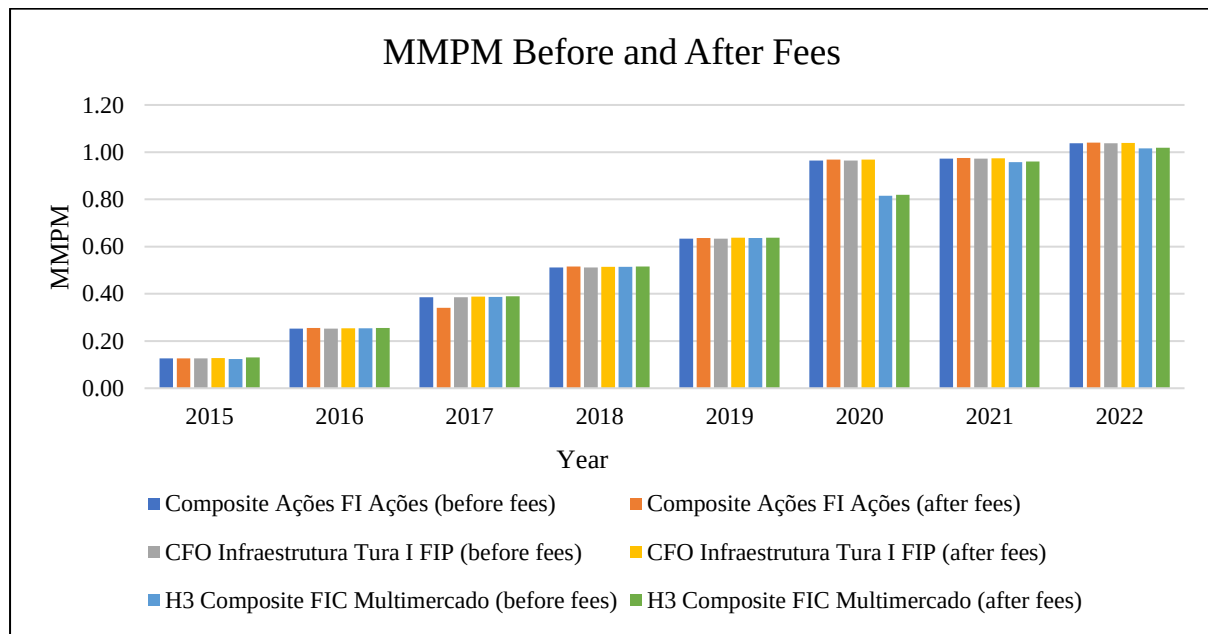


Figure 11 presents the MPPM results for investors with moderate risk tolerance, both before and after accounting for fees. The results indicate that the MPPM was positive for all portfolios, both before and after fees were considered.

Figure 11

Summary of manipulation-proof performance for moderate risk tolerance investors before and after fees

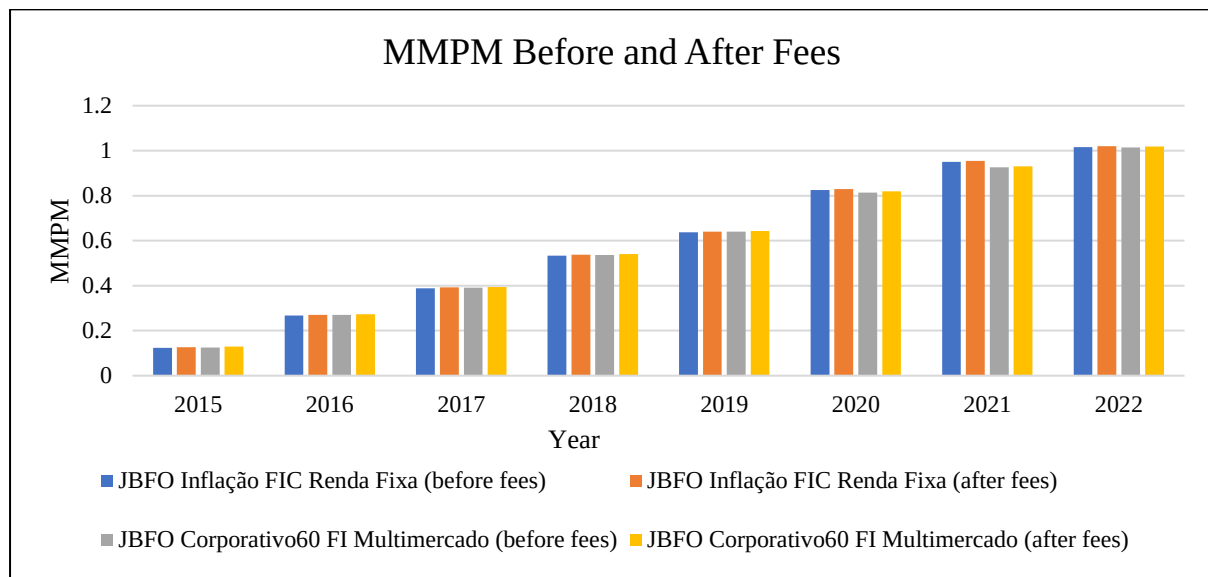
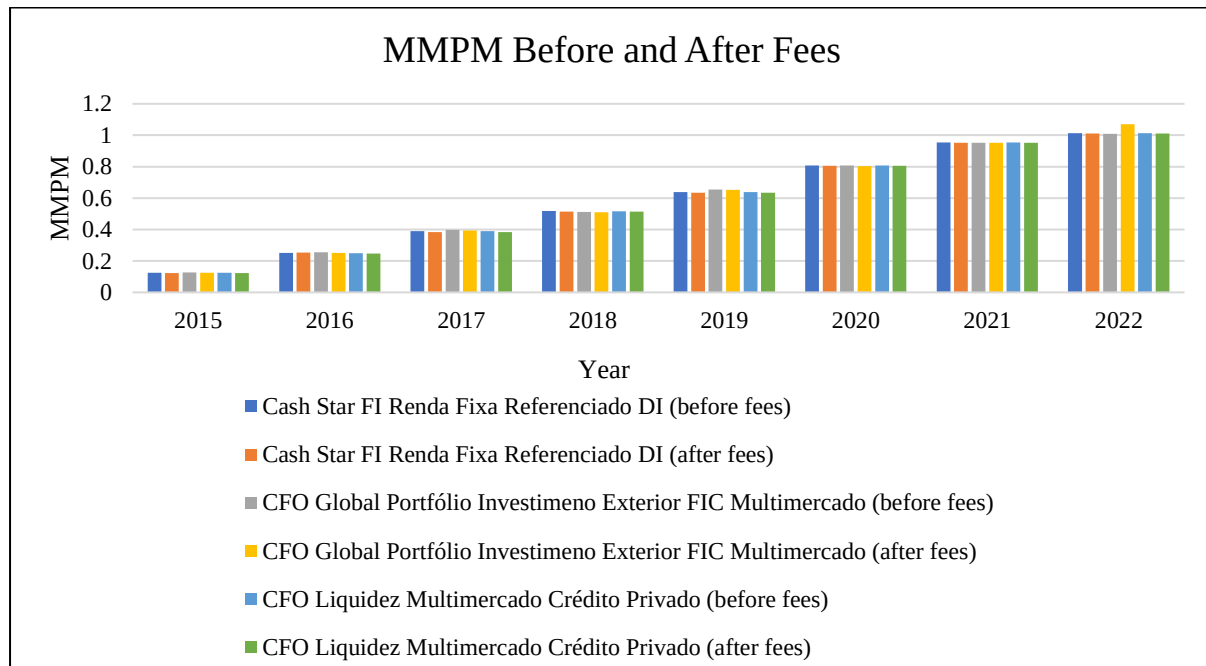


Figure 12 presents the MPPM results for investors with low risk tolerance, both before and after accounting for fees. The findings indicate that the MPPM was positive for all portfolios, both before and after fees were considered.

Figure 12

Summary of manipulation-proof performance for low risk tolerance investors before and after fees



4.2 India

FundsIndia was the chosen robo-advisor for India as there are few Indian robo-advisors that provide a full display of the recommended portfolio. The product ranges that are provided by FundsIndia are mutual funds, Systematic Investment Plans (SIP), equities (share trading), fixed deposits and SIP Insurance. To get a full list of the portfolios, the robo-advisor requires the user to sign up on the platform. There are funds that are actively managed that exist and others that are passively managed. At this point in time, each portfolio has different fees (FundsIndia, 2015).

Out of the 31 portfolios on FundsIndia, 15 portfolios were selected as these 15 portfolios were the only ones that met the period criteria of 2015 to 2022 together with the respective benchmark. Out of the 31 portfolios, 15 are for investors with high tolerance.

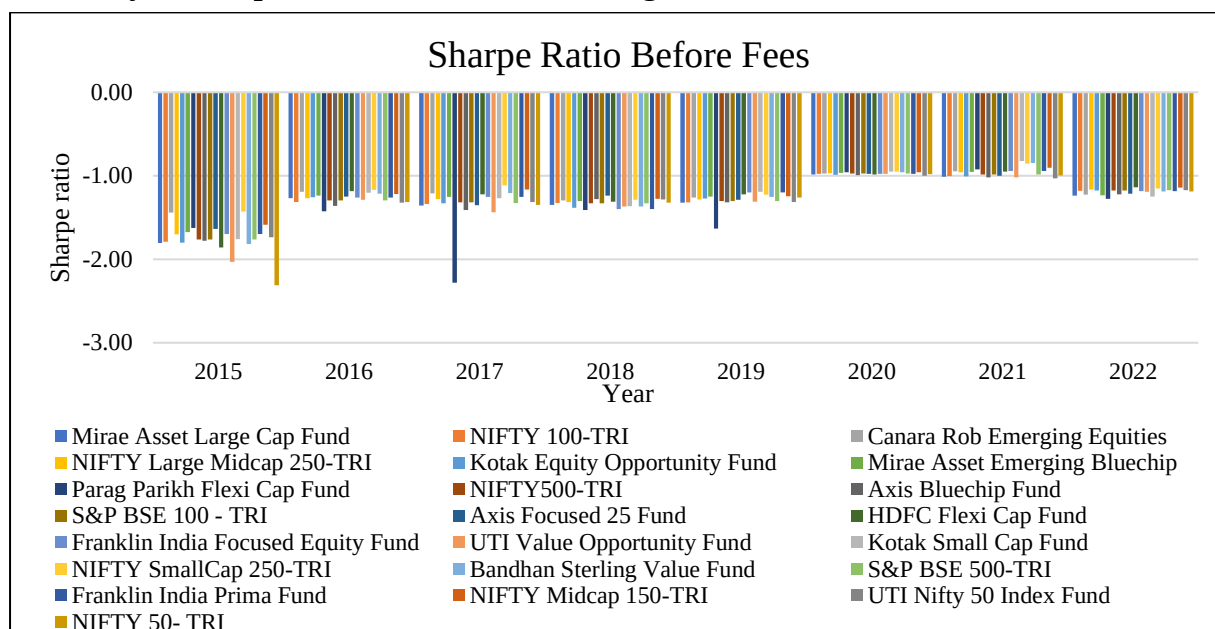
The results of the performance measures of the portfolios are reported in this section.

4.2.1 Sharpe ratio

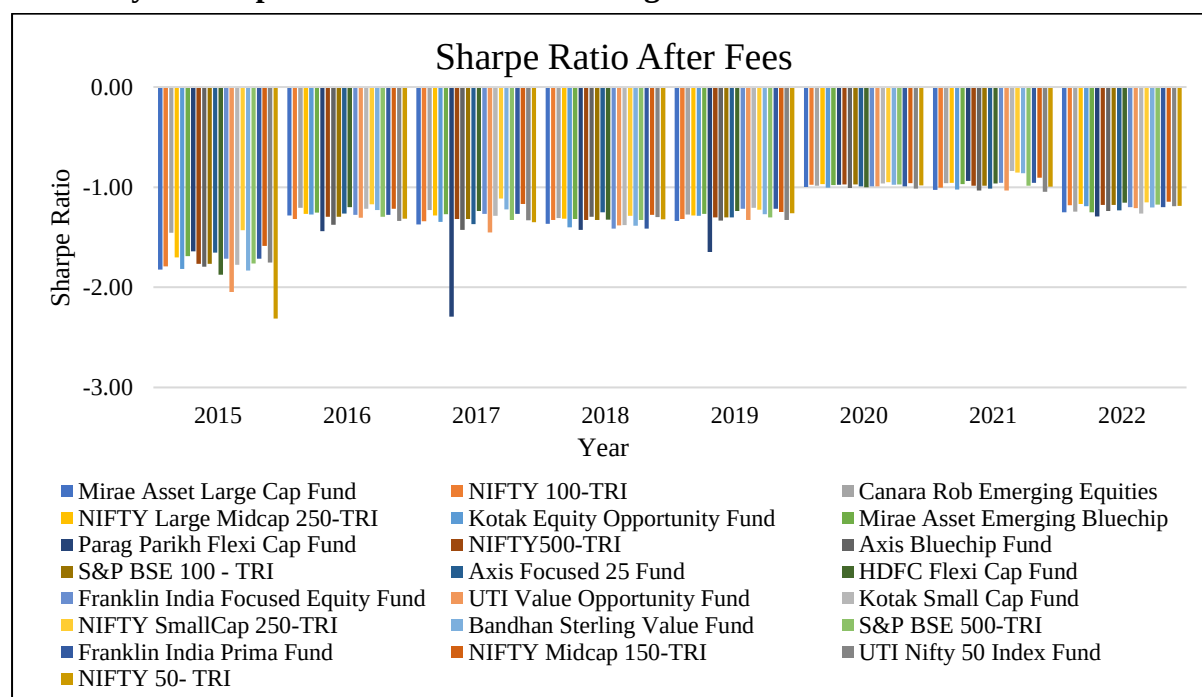
Figure 13 presents the Sharpe ratio results for investors with high risk tolerance, before fees were considered. The results indicate that all portfolios underperformed from 2015 to 2022. There were no significant performance differences between the portfolios and the benchmark, with the portfolios generally performing in line with the benchmark. The Parag Parikh Flexi Cap Fund was the portfolio with the worst Sharpe ratio in 2017.

Figure 13

Summary of Sharpe ratio for investors with high risk tolerance before fees

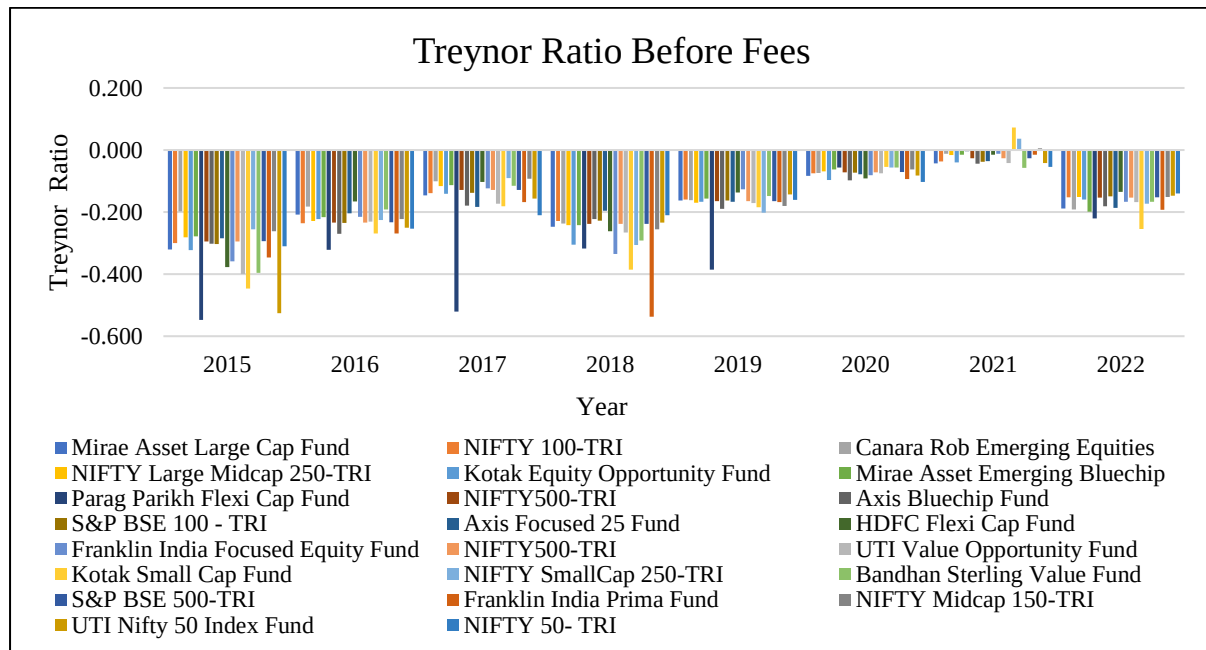


In **Figure 14**, the Sharpe ratio results for high-risk-tolerance investors are displayed after factoring in fees. It is evident from the results that all portfolios performed worse than the benchmark from 2015 to 2022. There were no performance variations between the portfolios and the benchmark. Post fee adjustment, the portfolio's performance saw a slight decrease.

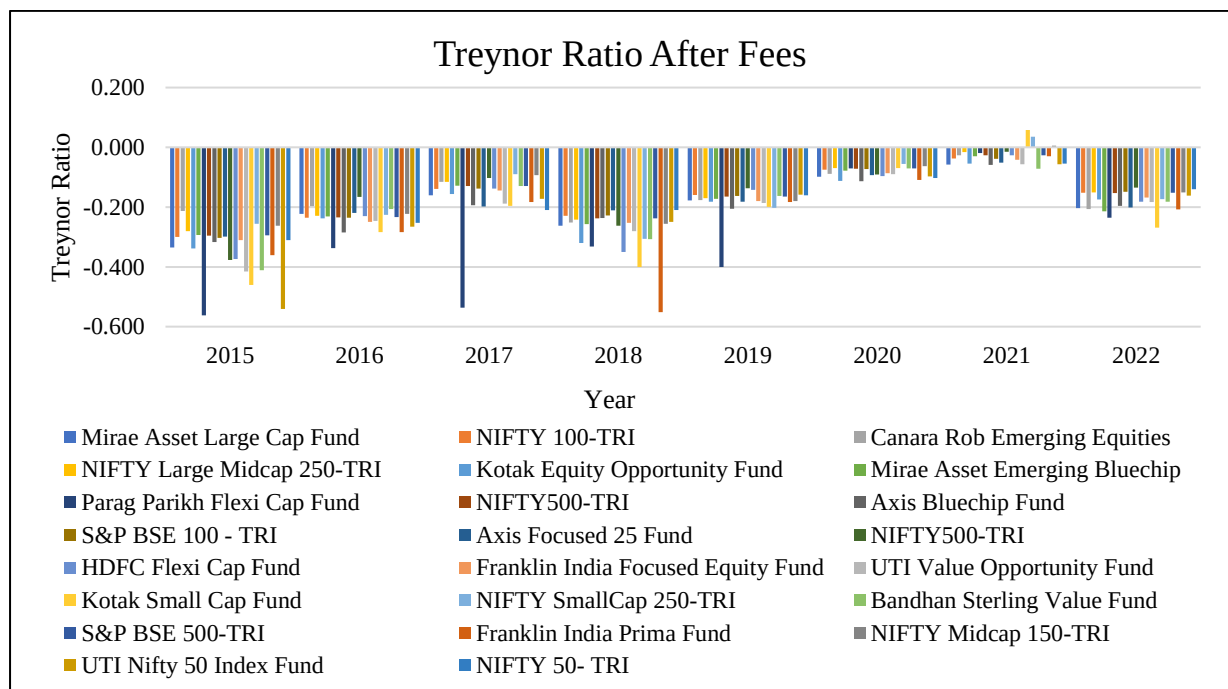
Figure 14**Summary of Sharpe ratio for investors with high risk tolerance after fees**

4.2.2 Treynor ratio

In the results shown in **Figure 15**, the Treynor ratio for investors with high risk tolerance was analysed without taking fees into account. All portfolios showed underperformance across all years, except for the Kotak Small Cap Fund, which slightly outperformed the benchmark in 2021. On the other hand, the Franklin India Prima Fund deviated from the benchmark in 2021. Generally, the performance of the portfolios aligned with the benchmarks.

Figure 15**Summary of Treynor ratio for investors with high risk tolerance before fees**

In the results shown in **Figure 16**, the Treynor ratio for investors with high risk tolerance was presented after taking fees into account. In all years, the portfolios showed lower performance compared to the benchmark, except for the Kotak Small Cap Fund which showed a slight outperformance in 2021. After factoring in fees, a slight decrease in performance was noted.

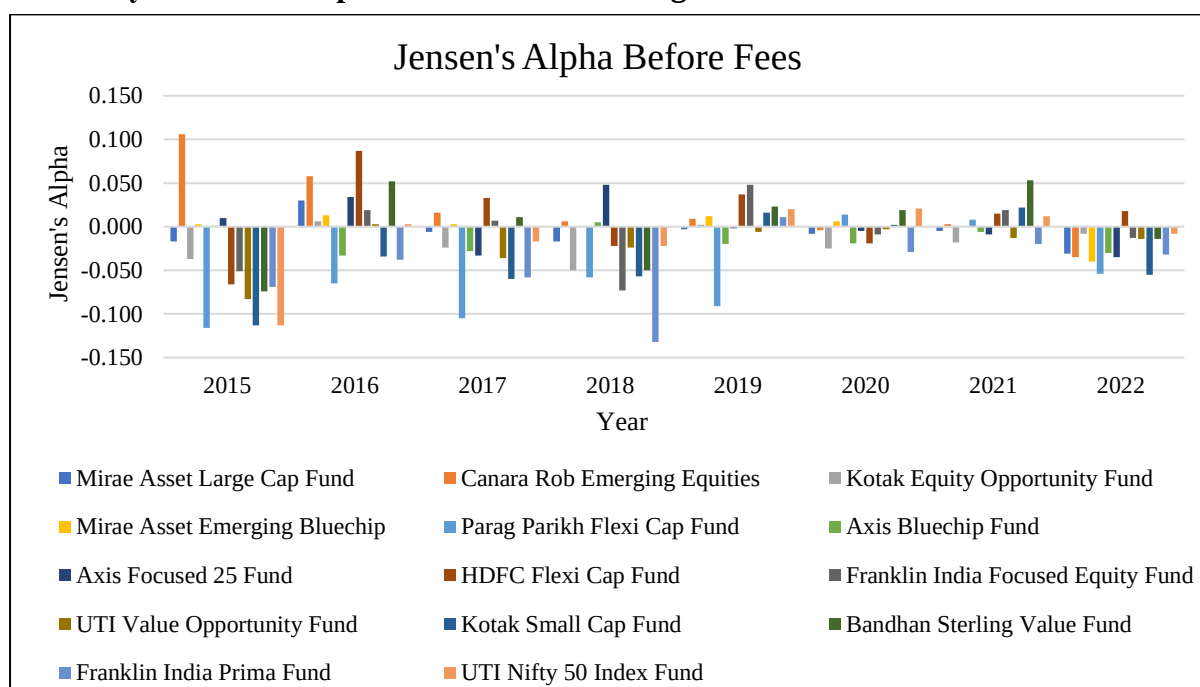
Figure 16**Summary of Treynor ratio for investors with high risk tolerance after fees**

4.2.3 Jensen's alpha

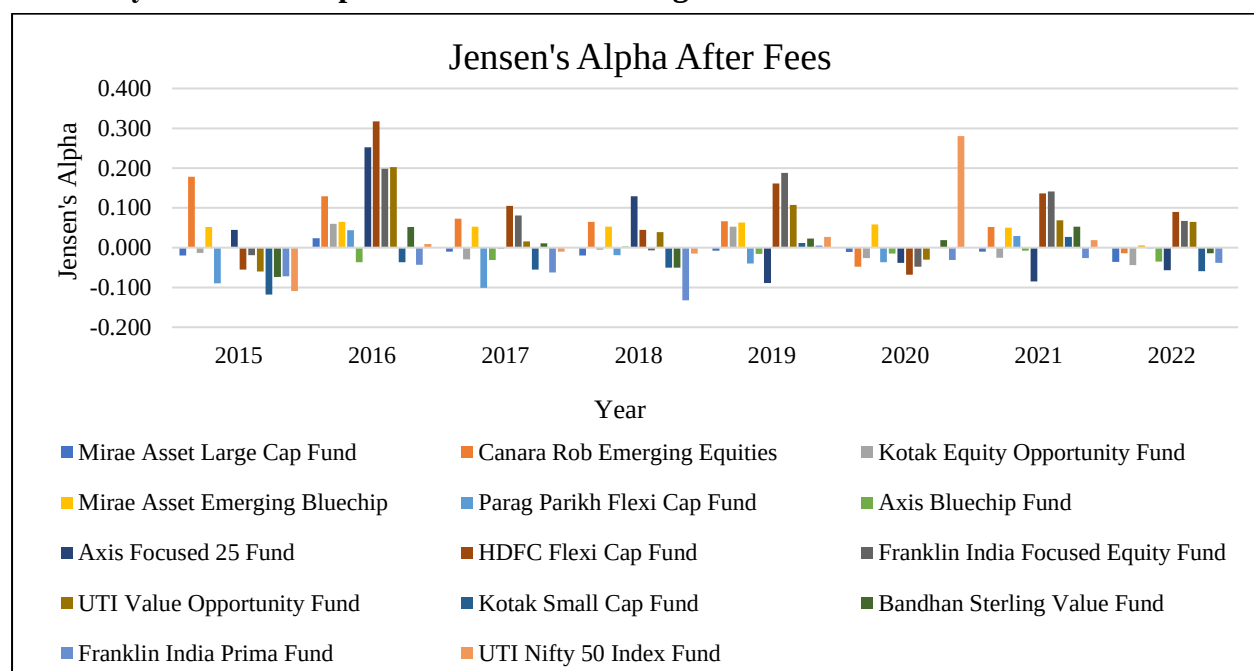
The results of Jensen's alpha for investors with high risk tolerance before fees were considered are displayed in **Figure 17**. In 2015, four portfolios marginally exceeded the benchmark, followed by 11 portfolios in 2016. Five portfolios exhibited slight outperformance in 2017 and 2020, while three portfolios did so in 2018. Nine portfolios outperformed the benchmark in 2019, and eight portfolios showed slight outperformance. In 2020, only one portfolio succeeded in outperforming the benchmark.

Figure 17

Summary of Jensen's alpha for investors with high risk tolerance before fees



In the Jensen's alpha results for investors with high risk tolerance before fees were considered, **Figure 18** shows that three portfolios slightly exceeded the benchmark in 2015. In 2016, 11 portfolios outperformed the benchmark, and in both 2017 and 2018, six portfolios outperformed the benchmark. In 2019, ten portfolios outperformed the benchmark, followed by nine portfolios in 2021. Additionally, in 2020, four portfolios displayed slight outperformance.

Figure 18**Summary of Jensen's alpha for investors with high risk tolerance after fees**

4.2.4 Manipulation-proof performance measure

The MPPM results for high-risk-tolerance investors before factoring in fees are shown in **Figure 19** and **Figure 20** shows results for high-tolerance investors after fees. These results demonstrate that the MPPM was favourable for all portfolios, both prior to and after fee adjustments.

Figure 19

Summary of the manipulation-proof performance for investors with high risk tolerance before fees

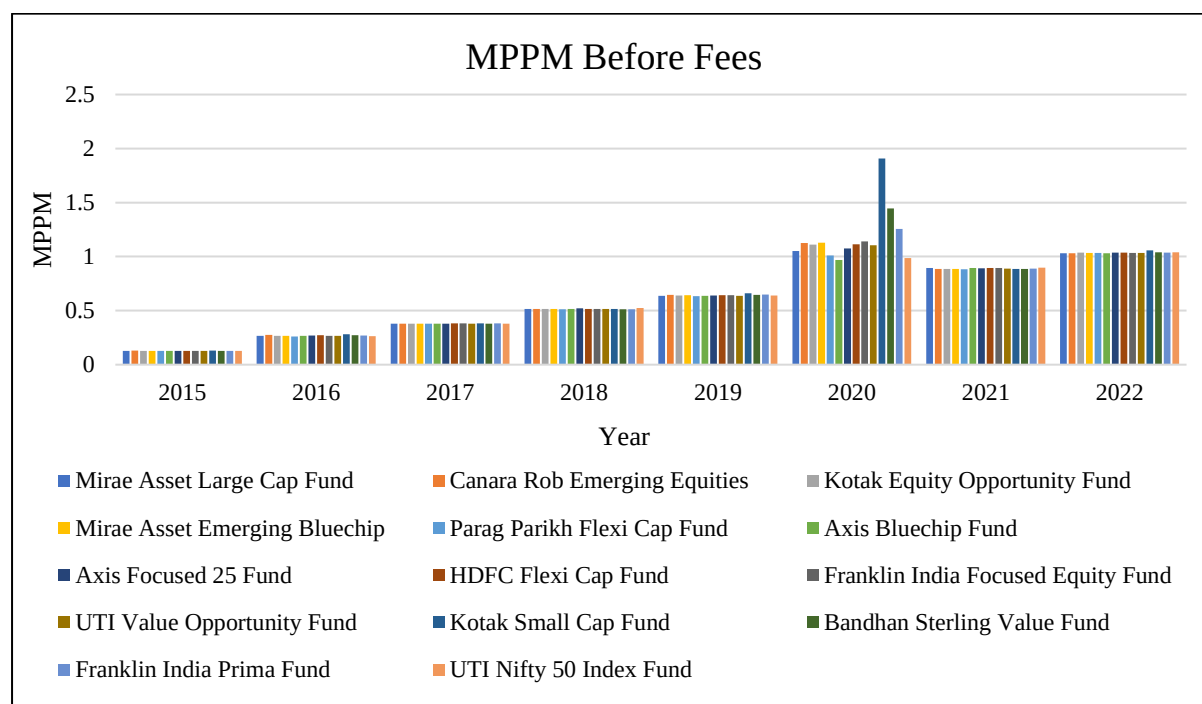
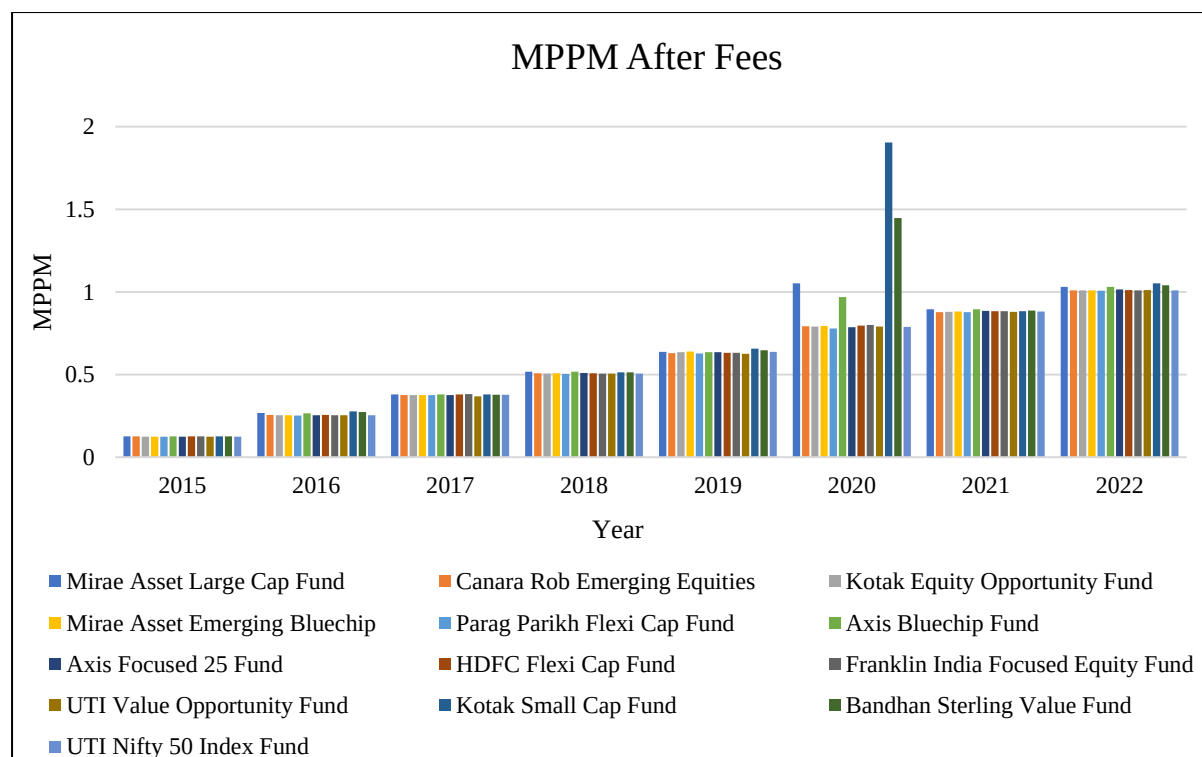


Figure 20

Summary of the manipulation-proof performance for investors with high risk tolerance after fees



4.3 China

Scalable Capital was the chosen robo-advisor for China. Scalable Capital offers services to citizens residing in Germany, Austria, Italy, Netherlands, France and Spain. Scalable Capital uses a broker service called JustETF and provides ETFs in China. It has a range of products such as savings plans, ETFs, exchange-traded products, cryptocurrency and derivatives. Furthermore, it provides three plan options. The Free broker provides all products and volume order of €250 or more are free of charge. Prime broker bills the user €2.99 monthly and saving plans without order fees on all products and the user receives an unlimited number of trades on a Gettex without paying order fees. Prime + Broker plan includes all benefits on Prime broker for €4.99 and a 2.6% interest on uninvested balances up to €100 000. Each recommended portfolio has a different flat fee that ranges from 0.20% to 0.65% depending on the asset class (Scalable Capital, n.d.)

Out of the 63 portfolios on Scalable Capital, 12 portfolios were selected as these 12 portfolios met the period criteria of 2015 to 2022 together with the respective benchmark. Out of the 12 portfolios, one portfolio is for risk averse investors, six are for moderate investors and five are for investors with high tolerance.

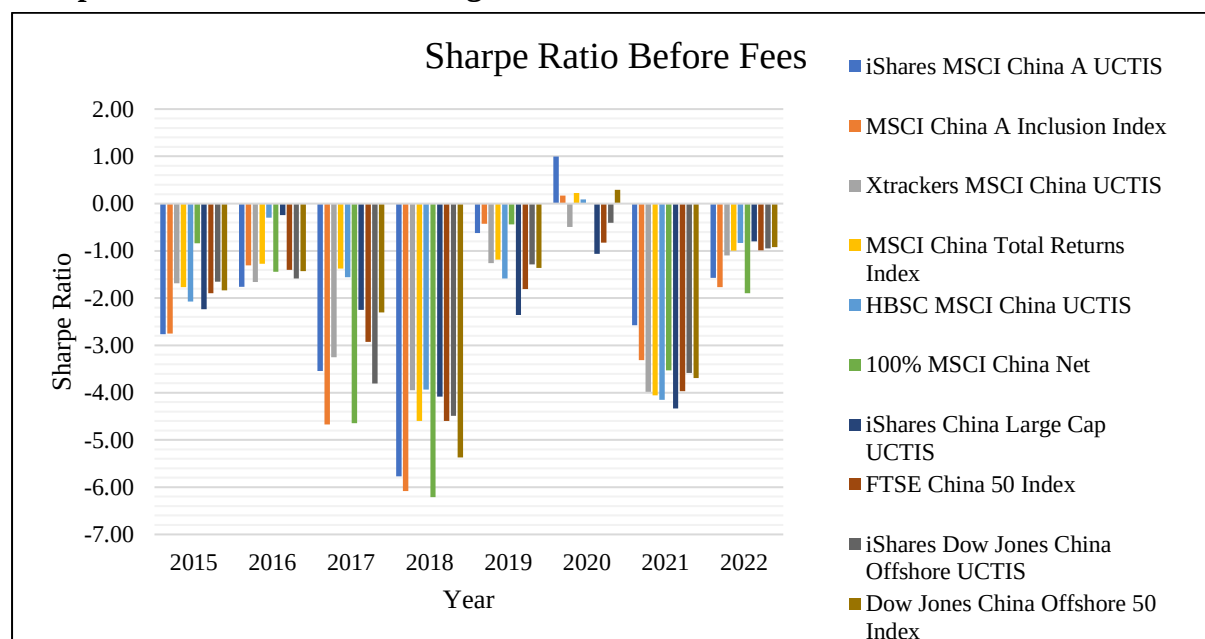
The results of the performance measures of the portfolios are reported in this section.

4.3.1 Sharpe ratio

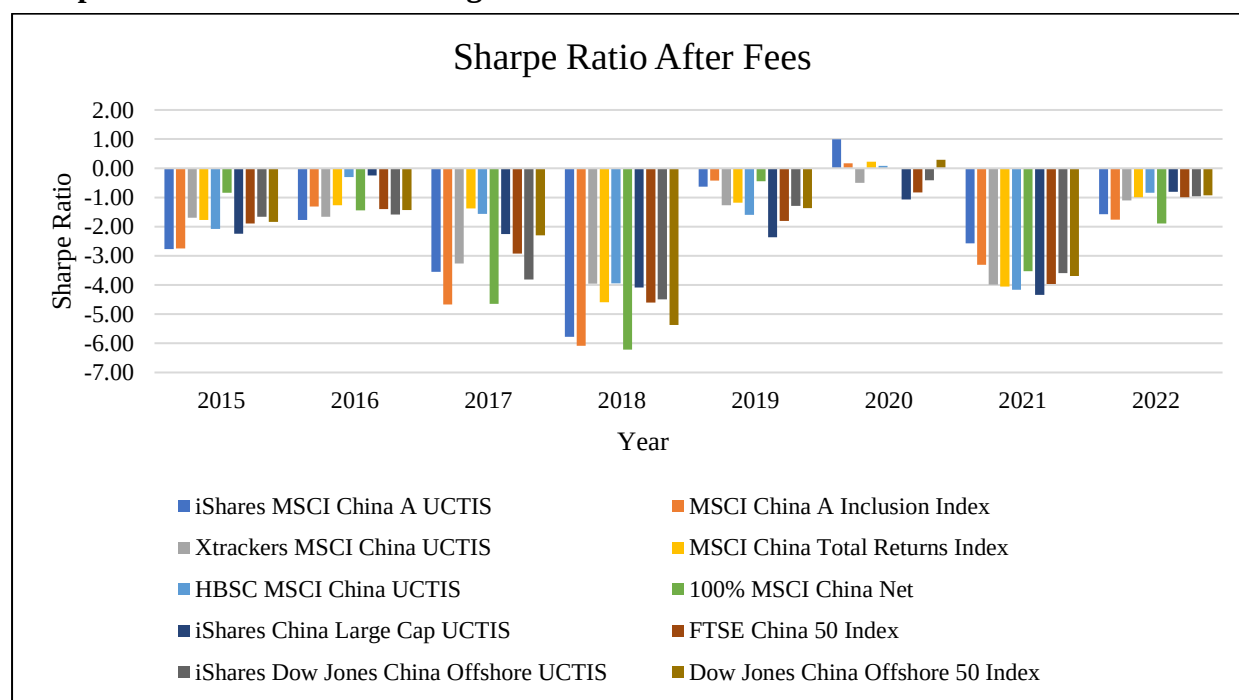
The results of the Sharpe ratio for investors with high risk tolerance before fees were considered are shown in **Figure 21**. From 2015 to 2022, the portfolios did not meet expectations, with the iShares MSCI China UCITS and HSBC MSCI China UCITS surpassing their respective benchmarks in 2020. Furthermore, in 2020, the iShares Dow Jones China Offshore UCITS and Xtrackers MSCI China UCITS showed deviations from their benchmarks in terms of performance. In general, the portfolios' performance closely matched that of the benchmarks.

Figure 21

Sharpe ratio for investors with high tolerance before fees



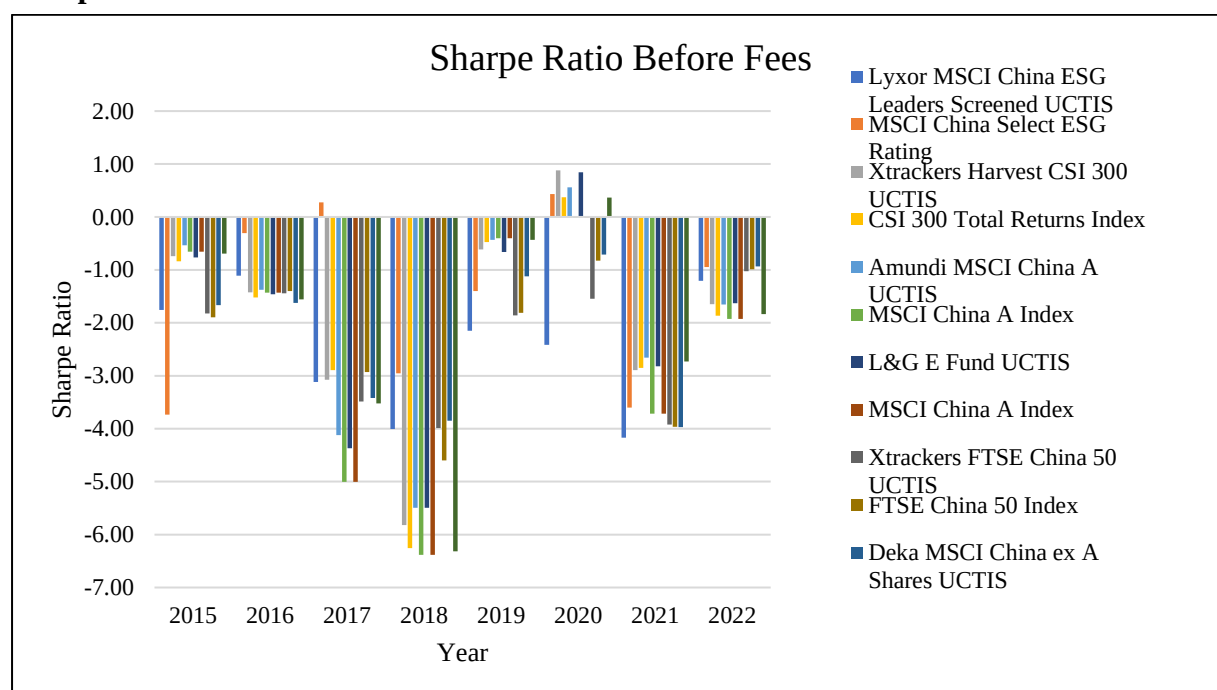
In the Sharpe ratio results shown in **Figure 22**, it is evident that even after factoring in fees, the portfolios for investors with high risk tolerance consistently lagged from 2015 to 2022. The iShares MSCI China UCITS managed to outperform its benchmark in 2020, but there was a slight decrease in performance when fees were considered. In general, the portfolios demonstrated performance that closely mirrored the benchmarks.

Figure 22**Sharpe ratio for investors with high tolerance after fees**

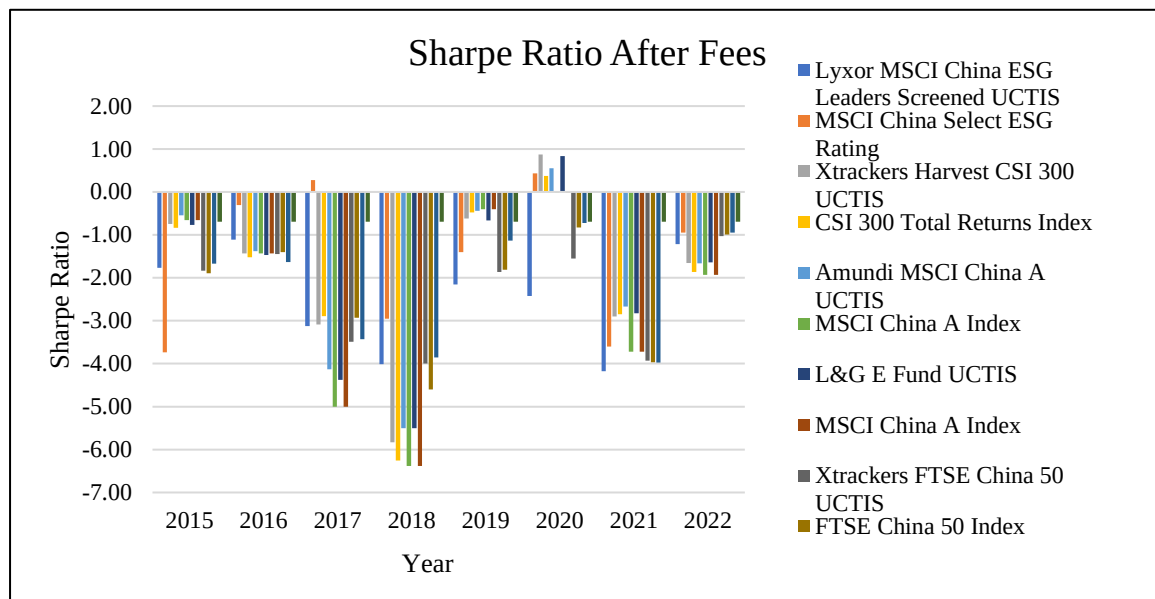
The Sharpe ratio results for investors with moderate risk tolerance before fees were depicted in **Figure 23**. The portfolios showed lower performance from 2015 to 2022. Nevertheless, the Xtrackers Harvest CSI 300 UCITS, Amundi MSCI China A UCITS, CSI 300 Total Returns Index, and L&G E Fund UCITS surpassed their respective benchmarks in 2020. On the other hand, the Lyxor MSCI China ESG Leaders Screened UCITS and Amundi MSCI China A UCITS displayed performance variations from their benchmarks in 2020. Overall, the portfolios' performance closely aligned with the benchmarks.

Figure 23

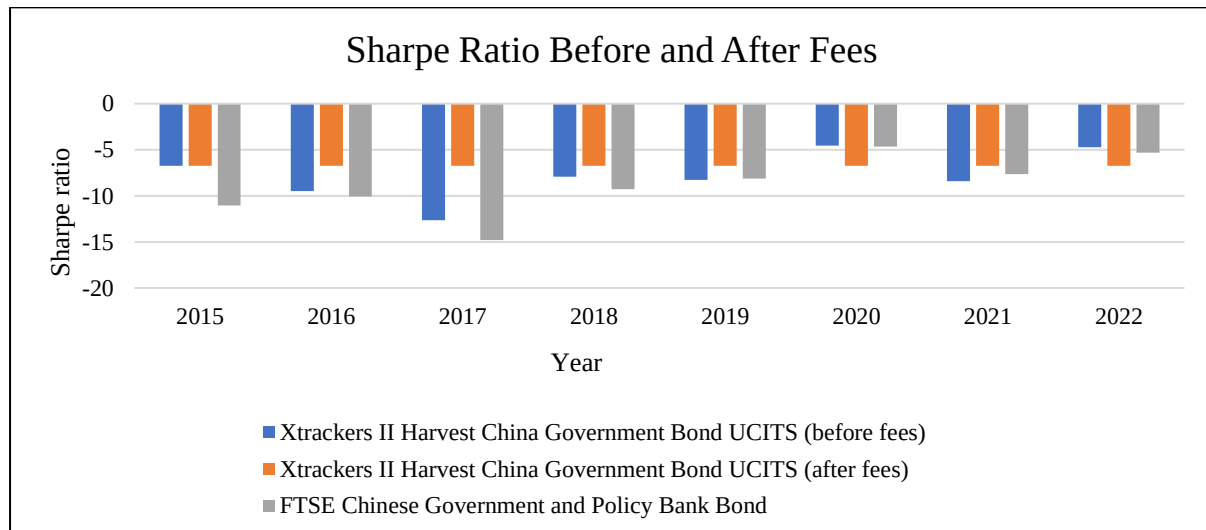
Sharpe ratio for investors with moderate risk tolerance before fees



The Sharpe ratio results for investors with moderate risk tolerance after factoring in fees are shown in **Figure 24**. The portfolios showed underperformance from 2015 to 2022, and this underperformance was further exacerbated after accounting for fees. In 2020, the Xtrackers Harvest CSI 300 UCITS, Amundi MSCI China A UCITS, and L&G E Fund UCITS outperformed their respective benchmarks. However, the Amundi MSCI China A UCITS and L&G E Fund UCITS did not consistently track with the benchmarks. Overall, the portfolios' performance generally remained in line with the benchmarks.

Figure 24**Sharpe ratio for moderate risk tolerance investors after fees**

In **Figure 25**, the Sharpe ratio findings for investors with low risk tolerance are displayed, showing results before and after factoring in fees. Portfolios showed lower performance compared to the benchmarks from 2015 to 2022, with performance closely tracking the benchmarks. After including fees, a decrease in performance was noted.

Figure 25**Sharpe ratio for low risk tolerance investors before and after fees**

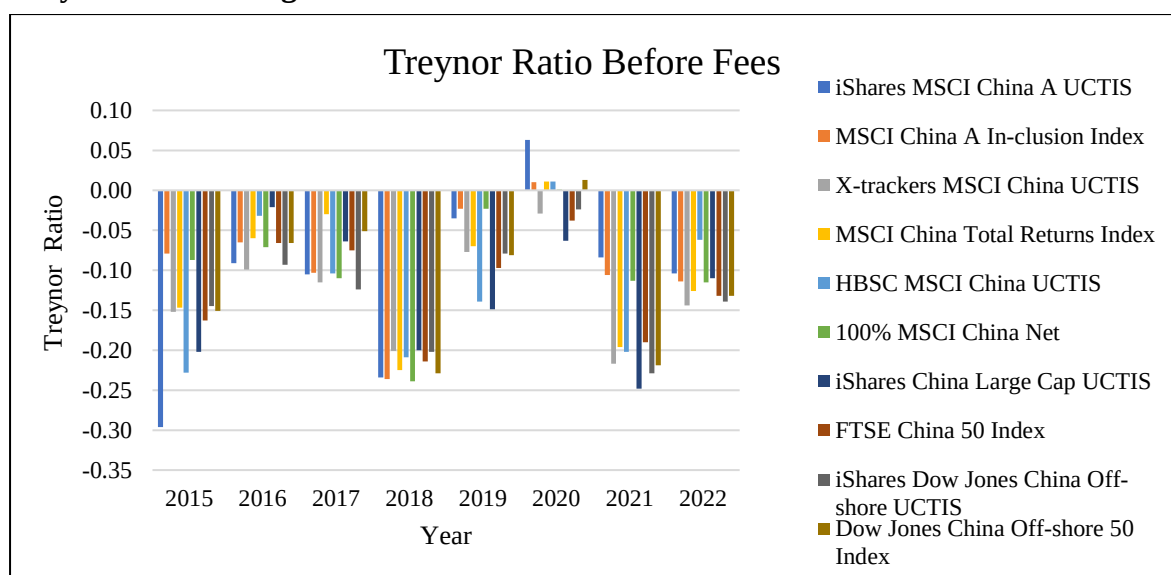
4.3.2 Treynor ratio

The results of the Treynor ratio for investors with moderate risk tolerance before fees are shown in **Figure 26**. From 2015 to 2022, the Treynor ratio was in the negative territory, which

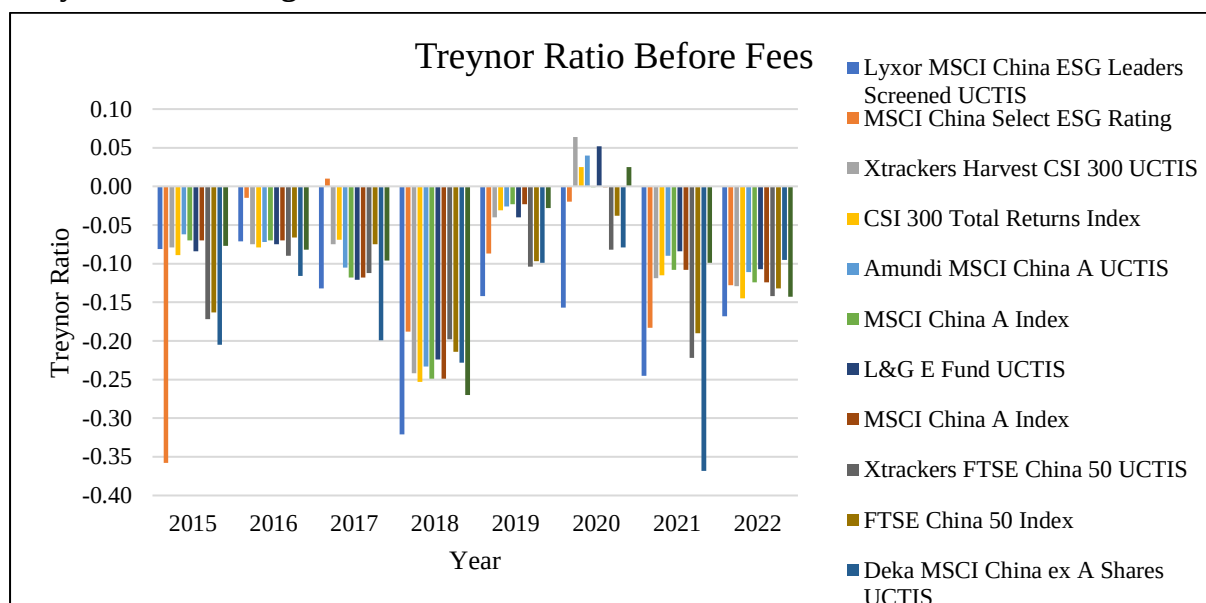
indicates that the portfolios did not perform well relative to the risk taken. However, in 2020, the iShares MSCI China A UCITS and HSBC MSCI China UCITS showed better performance. On the other hand, the iShares Dow Jones China and Xtrackers MSCI China did not match the benchmark in 2020. Overall, the portfolios demonstrated similar performance to the benchmark.

Figure 26

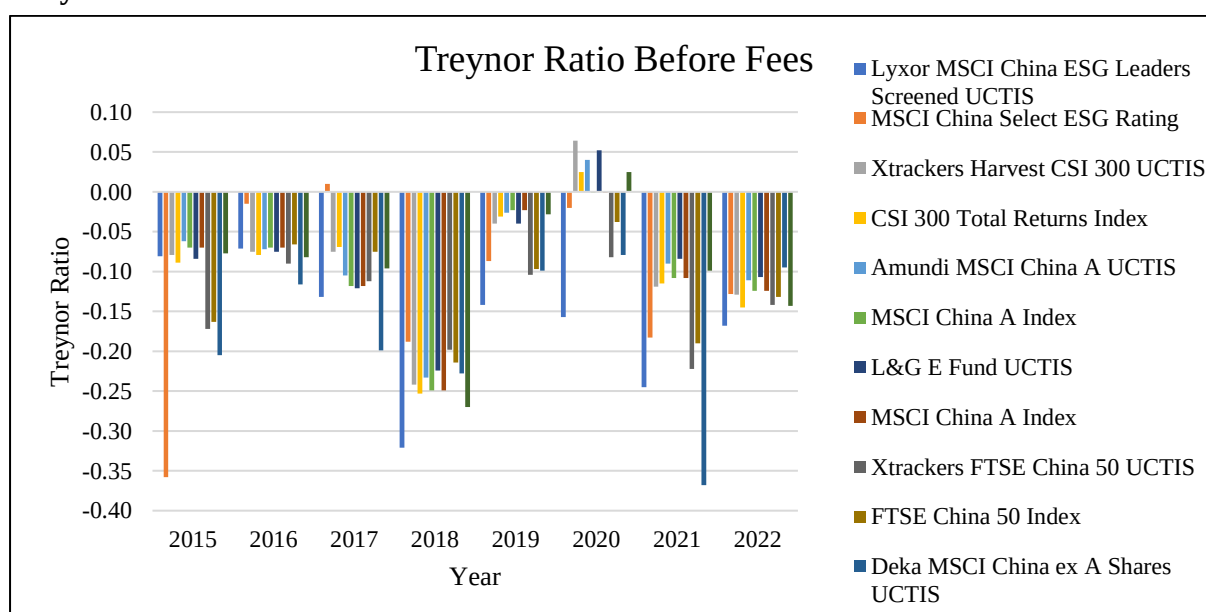
Treynor ratio for high risk tolerance investors before fees



In the results shown in **Figure 27**, the Treynor ratio for investors with high risk tolerance indicates that the portfolios consistently performed below the expected level relative to the risk taken from 2015 to 2022, even after factoring in fees. The iShares MSCI China UCITS and HSBC MSCI China UCITS managed to outperform their respective benchmarks in 2020. However, the iShares Dow Jones China, Xtrackers MSCI China, and HSBC MSCI China UCITS did not mirror the benchmarks in 2020. Furthermore, the portfolio's performance decreased once fees were taken into account.

Figure 27**Treynor ratio for high risk tolerance investors after fees**

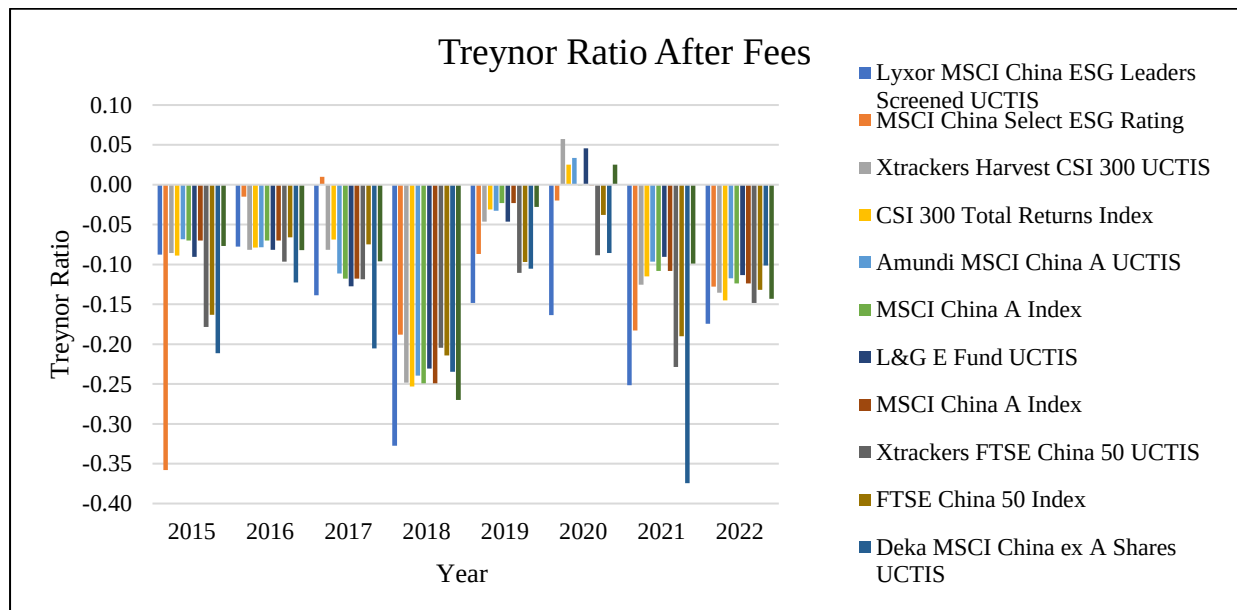
The results of the Treynor ratio for investors with moderate risk tolerance before fees were shown in **Figure 28**. From 2015 to 2022, the portfolios did not perform as well as the risk taken. In 2020, the Xtrackers Harvest CSI 300, Amundi MSCI China A UCITS, and L&G E Fund UCITS slightly outperformed their benchmarks. There were performance differences from the benchmarks in 2020 for the Deka MSCI China ex A Shares UCITS, Amundi MSCI China A UCITS, and L&G E Fund UCITS. Overall, the portfolios had similar performance to the benchmarks.

Figure 28**Treynor ratio for moderate risk tolerance investors before fees**

The results of the Treynor ratio for investors with moderate risk tolerance after factoring in fees are shown in **Figure 29**. Portfolio performance decreased once fees were considered. In 2020, the Xtrackers Harvest CSI 300 and Amundi MSCI China A UCITS exceeded the benchmark, while the Amundi MSCI China A UCITS and L&G E Fund UCITS did not match the benchmark. Overall, the portfolios demonstrated similar performance to the benchmark.

Figure 29

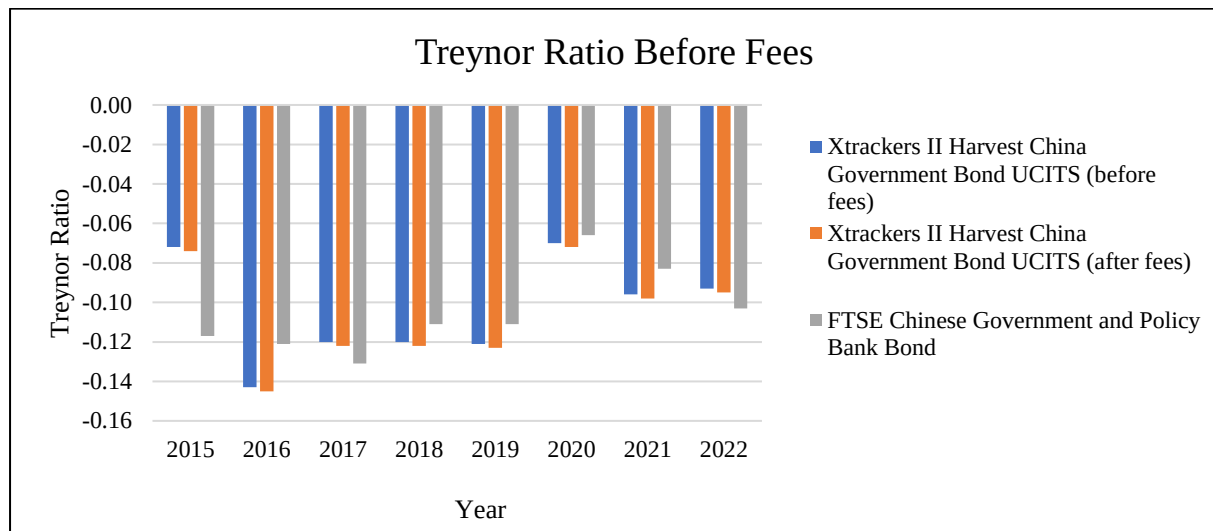
Treynor ratio for moderate risk tolerance investors after fees



In **Figure 30**, the Treynor ratio outcomes are presented for investors with a low risk tolerance, both before and after factoring in fees. The portfolio showed lower performance from 2015 to 2022, with no discernible performance variance compared to the benchmark. The portfolio's performance closely mirrored that of the benchmark, with a slight decrease in performance after accounting for fees.

Figure 30

Treynor ratio for investors with low tolerance before and after fees

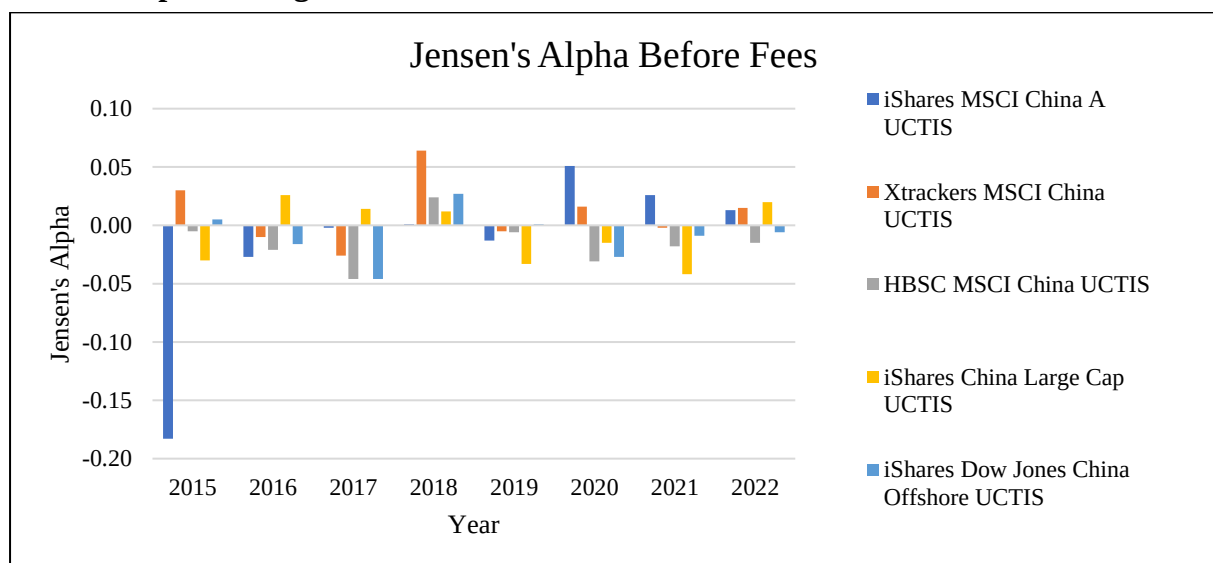


4.3.3 Jensen's alpha

In the results for Jensen's alpha in **Figure 31**, it can be observed that before factoring in fees, investors with high-risk tolerance had two out of five portfolios that marginally outperformed their respective benchmarks from 2015 to 2017 and in 2020. In 2018, all portfolios slightly exceeded the benchmark. Furthermore, in each year from 2019 to 2021, one portfolio surpassed the benchmark, and in 2022, three out of five portfolios outperformed the benchmark.

Figure 31

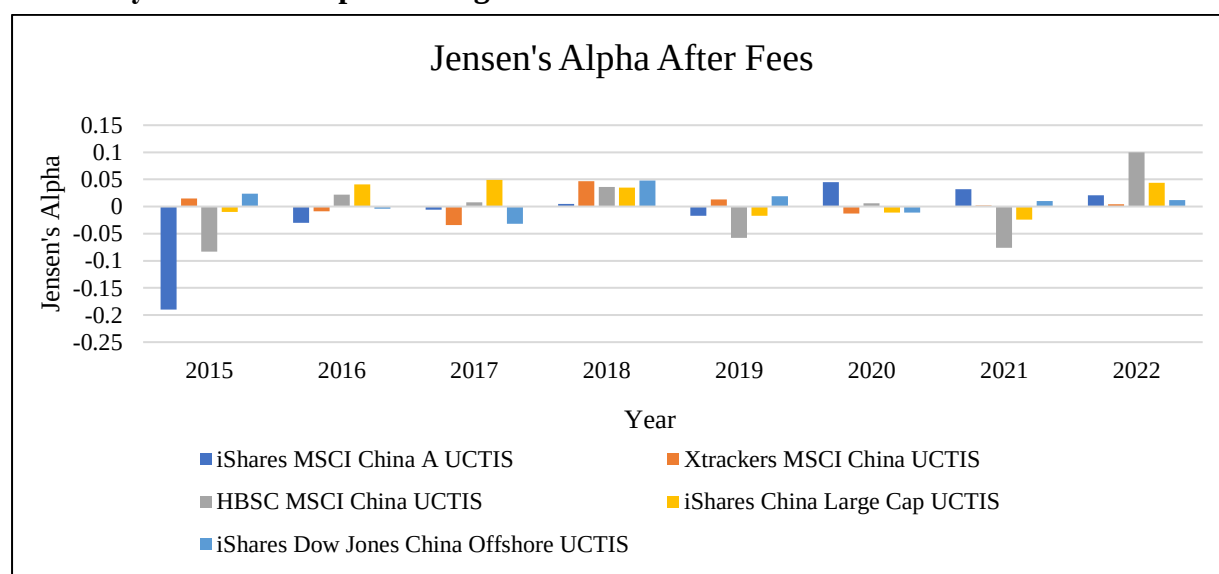
Jensen's alpha for high risk tolerance investors before fees



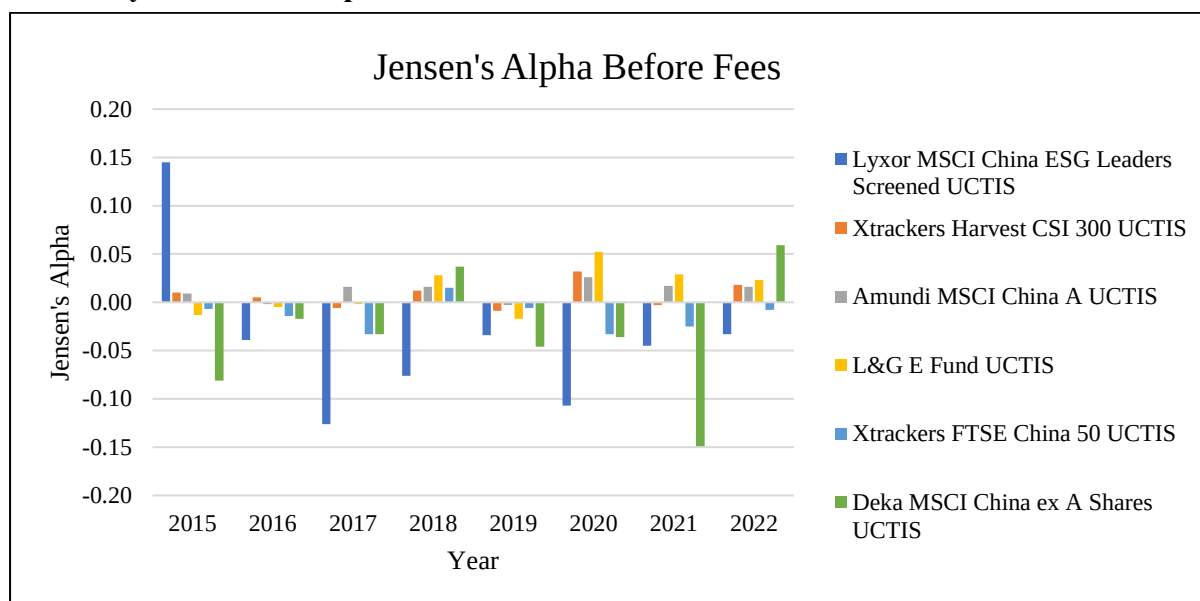
In the results of Jensen's alpha for high-risk tolerance investors, as shown in **Figure 32**, two out of five portfolios marginally exceeded their benchmarks after accounting for fees from 2015 to 2017, and in 2019 and 2020. In 2018 and 2022, all portfolios slightly outperformed their benchmarks, while in 2021, three out of five portfolios surpassed the benchmark by a small margin.

Figure 32

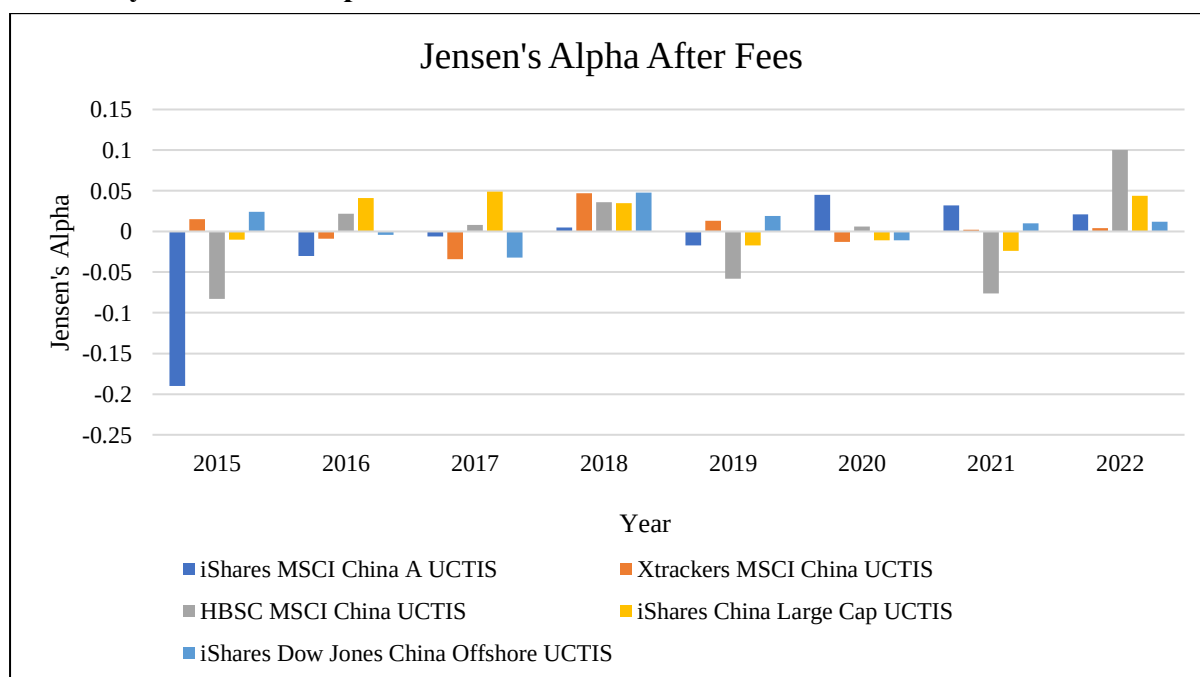
Summary of Jensen's alpha for high risk tolerance investors after fees



The results of Jensen's alpha for investors with moderate risk tolerance are depicted in **Figure 33**, both before and after fees were factored in. Out of six portfolios, three outperformed the benchmark in 2015 and 2022. During 2016 and 2017, one portfolio each year surpassed the benchmark. In 2018, five portfolios performed better than the benchmark, whereas in 2019, all portfolios fell short. Four portfolios outperformed the benchmark in 2021, and the same number did so again in 2022.

Figure 33**Summary of Jensen's Alpha for moderate tolerance investors before fees**

In the results for Jensen's alpha shown in **Figure 34**, after accounting for fees, five portfolios outperformed the benchmarks in 2015 and 2018. From 2016 to 2020, as well as in 2019, four portfolios outperformed the benchmark. In 2021, three portfolios outperformed, and in 2022, all portfolios outperformed the benchmark.

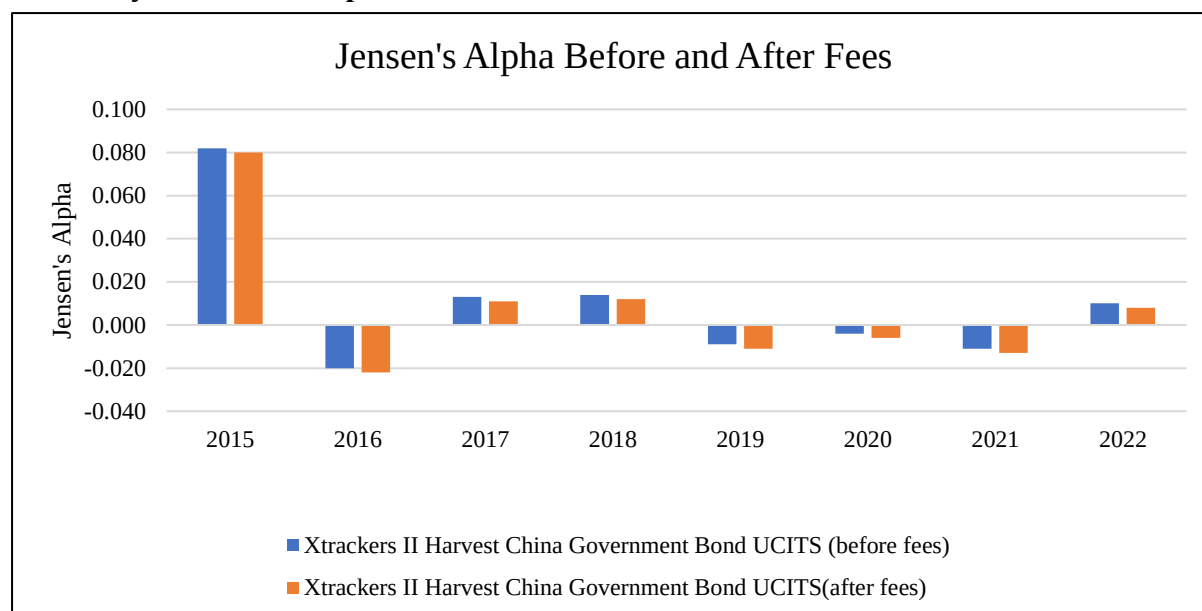
Figure 34**Summary of Jensen's Alpha for moderate tolerance investors after fees**

In **Figure 35**, the Jensen's alpha outcomes for investors with low risk tolerance are displayed, showing performance before and after fees were factored in. Throughout the period of 2015 to

2022, the portfolio demonstrated a slight outperformance compared to the benchmark, both prior to and after the inclusion of fees.

Figure 35

Summary of Jensen's Alpha for low tolerance investors before and after fees

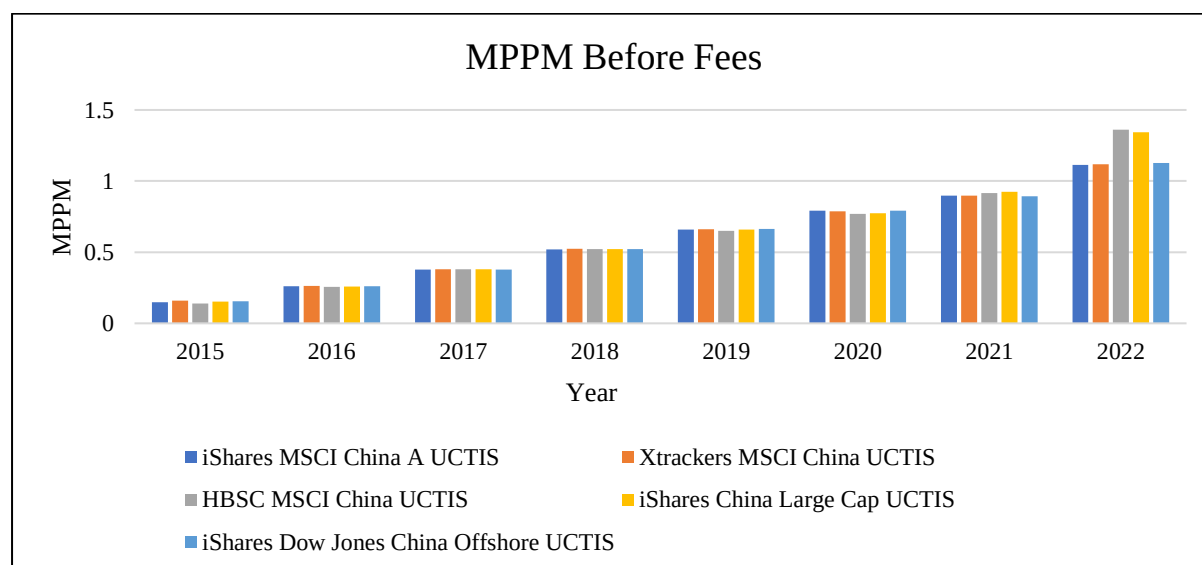


4.3.4 Manipulation-proof performance measure

The results for investors with high risk tolerance before fees were considered are shown in **Figure 36**, displaying the manipulation-proof performance measure (MPPM) outcomes. Over the years, the MPPM stayed positive, showing a small rise annually. The portfolios showed moderate performance and steered clear of tactics that could artificially boost conventional performance indicators.

Figure 36

Summary of manipulation-proof performance measure for high risk tolerance investors before fees



In the results shown in **Figure 37**, the manipulation-proof performance measure (MPPM) for investors with high risk tolerance remained positive after considering fees. Each year, there was a small increase in MPPM, but a slight decrease in performance was noted once fees were factored in.

Figure 37

Summary of manipulation-proof performance measure for high risk tolerance investors after fees

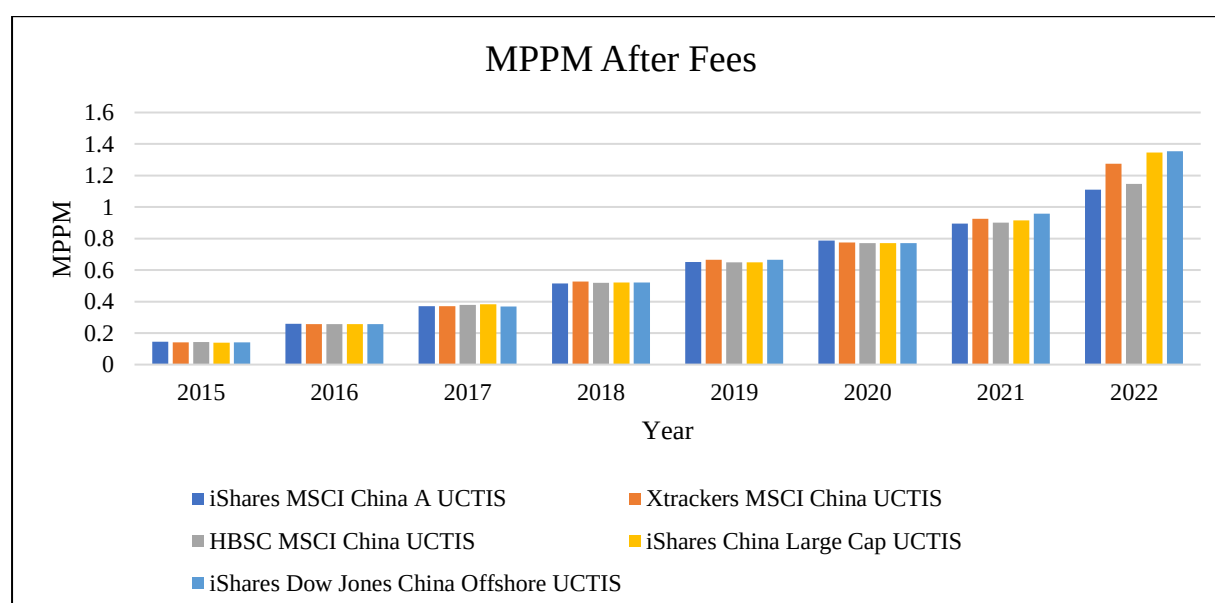


Figure 38 reports the MPPM results for investors with a moderate risk tolerance before fees are considered. The MPPM was positive for all the years and slightly increased with each year.

Figure 38

Summary of manipulation-proof performance measure for moderate risk tolerance investors before fees

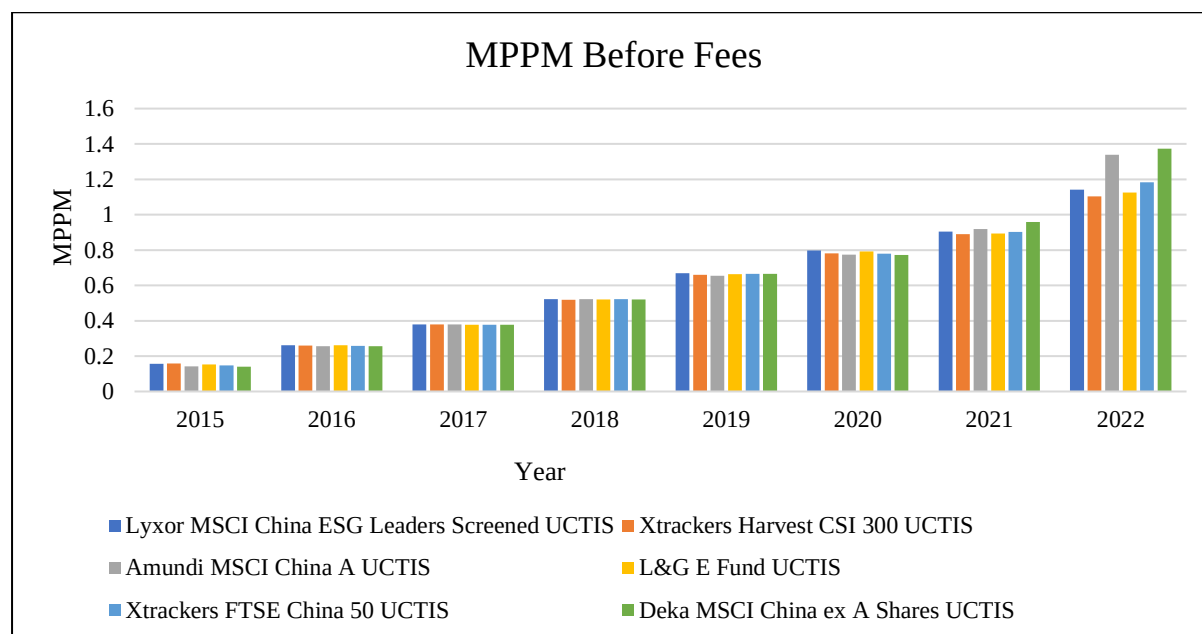


Figure 39 reports the MPPM results for investors with a moderate risk tolerance after fees have been considered. The MPPM still remained positive. However, there was a slight reduction after fees were considered.

Figure 39

Summary of manipulation-proof performance measure for moderate risk tolerance investors after fees

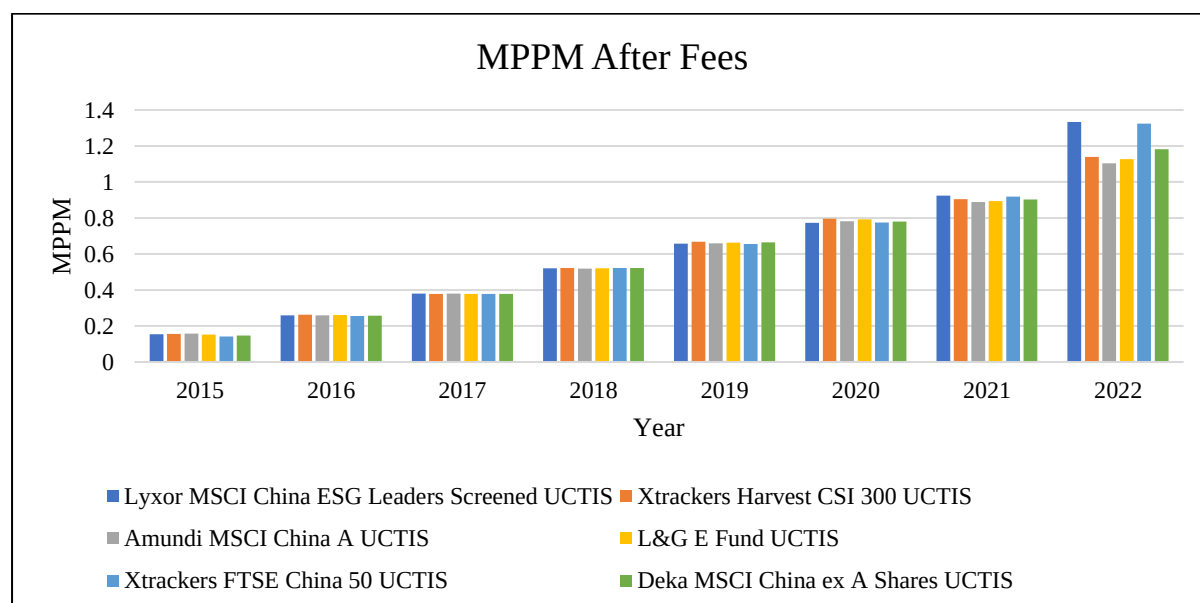
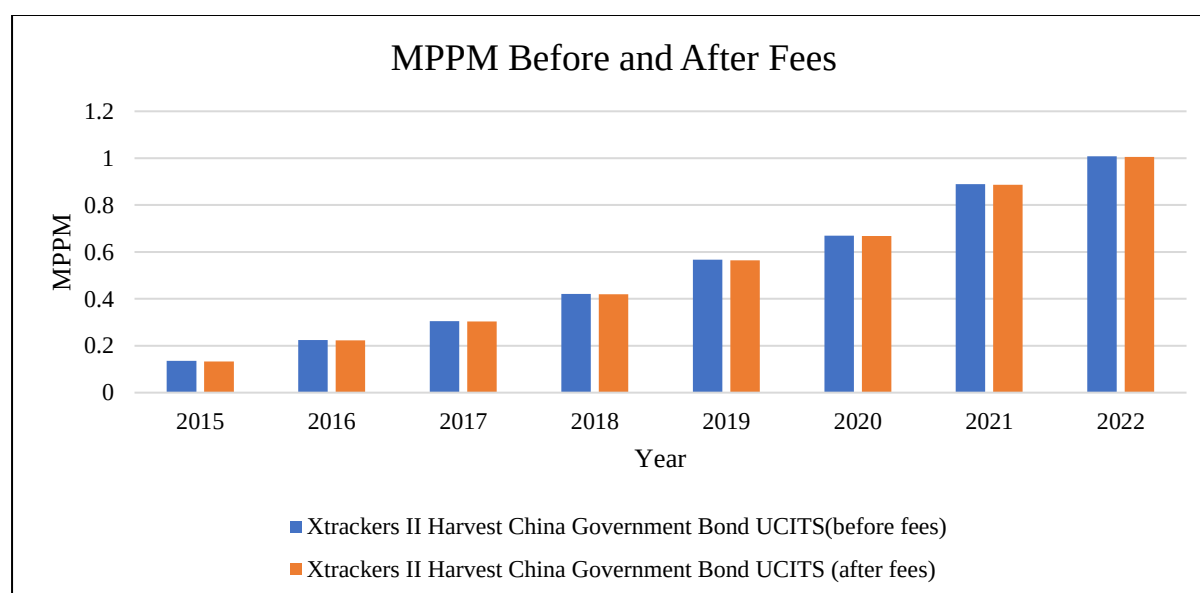


Figure 40 reports the MPPM results for investors with a low risk tolerance before and after fees have been considered. The MPPM still remained positive before and after fees were considered. However, there was a slight reduction after fees were considered.

Figure 40

Summary of manipulation-proof performance measure for low risk tolerance investors before and after fees



4.4 South Africa

Sygnia was the chosen robo-advisor for South Africa and has a product range such as retirement annuities, tax-free savings, internal and external unit trusts and provides a detailed summary of the recommended portfolios. Furthermore, it provides the risk level of each portfolio, a detailed description of the fee structure and asset class exposure. To use the platform, a user signs up on the platform and completes a questionnaire and based on the answers in the questionnaire, it will recommend a portfolio or a set of portfolios (Sygnia, n.d.).

Out of the 88 portfolios on Sygnia, 24 portfolios were selected as these 24 portfolios met the period criteria of 2015 to 2022 together with the respective benchmark. Out of the 24 portfolios, seven portfolios are for risk averse investors, five portfolios are for moderate investors and 12 portfolios are for investors with a high tolerance.

The results of the performance measures of the portfolios are reported in this section.

4.4.1 Sharpe ratio

The Sharpe ratios for the different risk tolerances from 2015 to 2022 will be presented in this section. **Figure 41** reports the Sharpe ratio results for investors with a high risk tolerance before fees are considered. In 2015& 2016, 3 of the 12 had positive Sharpe ratios. The years 2017 and 2021 had all portfolios with positive Sharpe ratio. In 2019, 5 of the 12 portfolios had a positive Sharpe ratio and 2020 had 8 of the 12 portfolios with positive Sharpe ratios. Portfolio performance remains consistent and like the portfolio throughout the years.

Figure 41

Summary of Sharpe ratios for investors with high risk tolerance before fees

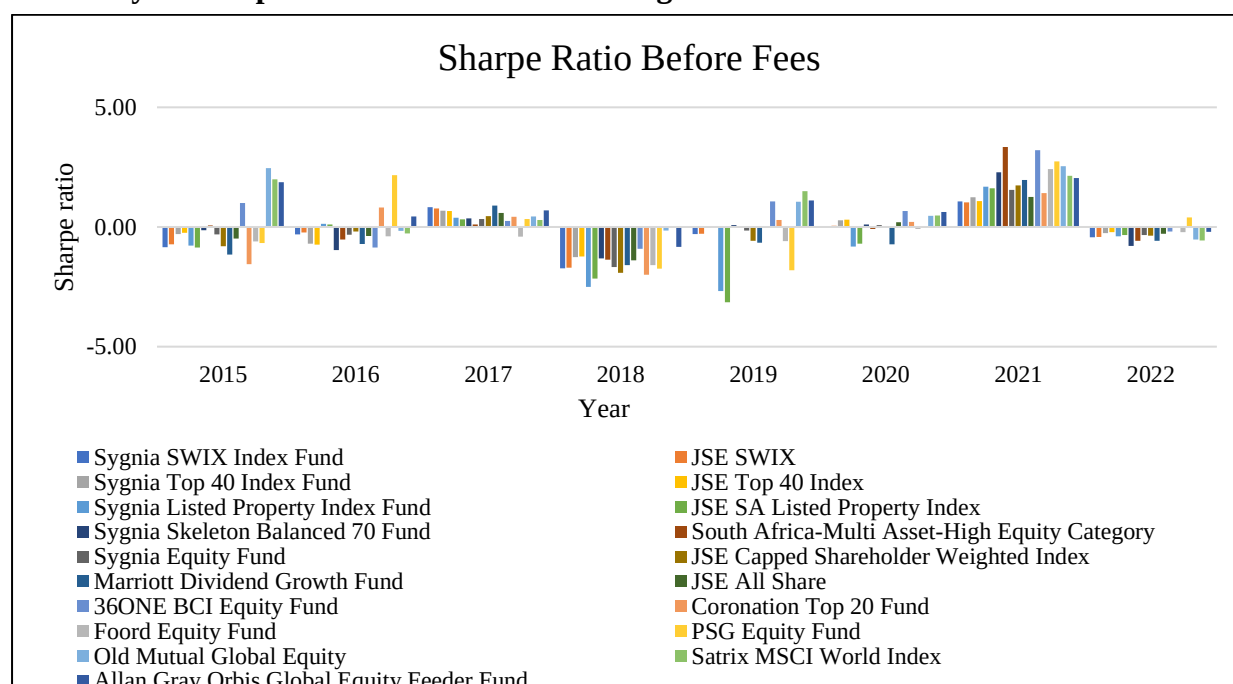


Figure 42 reports the Sharpe ratio results for investors with a high risk tolerance after fees are considered. In 2015& 2016, 3 of the 12 portfolios had a positive Sharpe ratio. The years 2017 and 2021 had all portfolios with positive Sharpe ratio. In 2019, 4 of the 12 portfolios had a positive Sharpe ratio and 2020 had 8 of the 12 portfolios with positive Sharpe ratios. 2022 had 1 portfolio with a positive Sharpe ratio. Portfolio performance slightly reduced after fees were considered. However, remains consistent and like the benchmark throughout the years.

Figure 42

Summary of Sharpe ratios for investors with high risk tolerance after fees

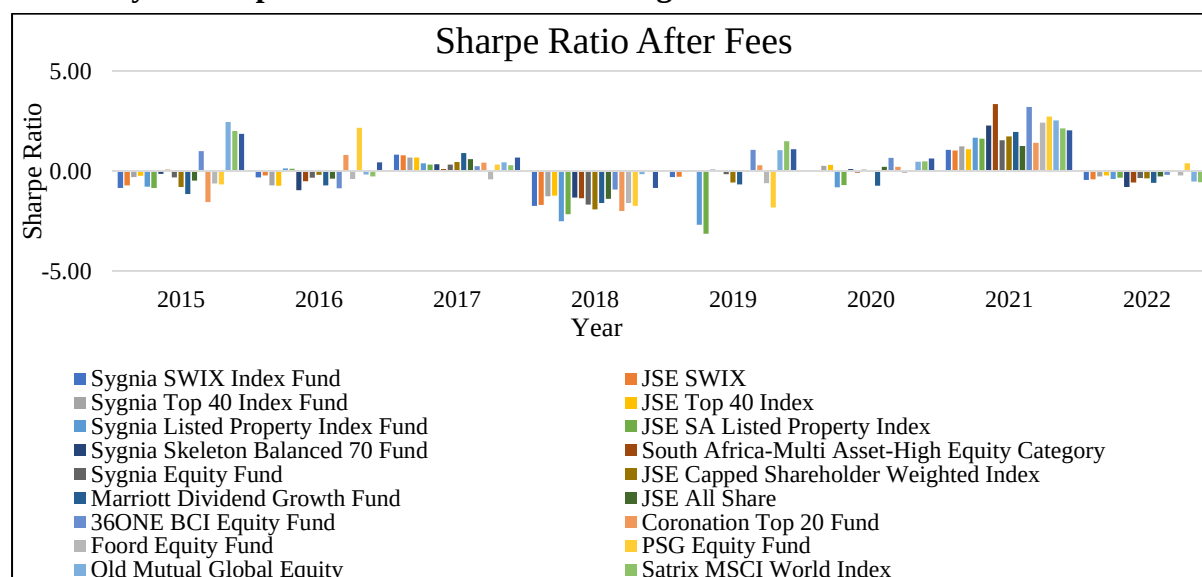


Figure 43 reports the Sharpe ratio results for investors with a moderate tolerance before fees were considered. In 2016, 4 of the 5 portfolios had a positive Sharpe ratio. The years 2017 and 2021 had all portfolios with positive Sharpe ratio. In 2019 and 2020, 3 of the 5 portfolios had a positive Sharpe ratio. 2022 had 1 portfolio with a positive Sharpe ratio. Portfolio performance remains consistent and like the benchmark throughout the years.

Figure 43

Summary of Sharpe ratio for investors with moderate risk tolerance before fees

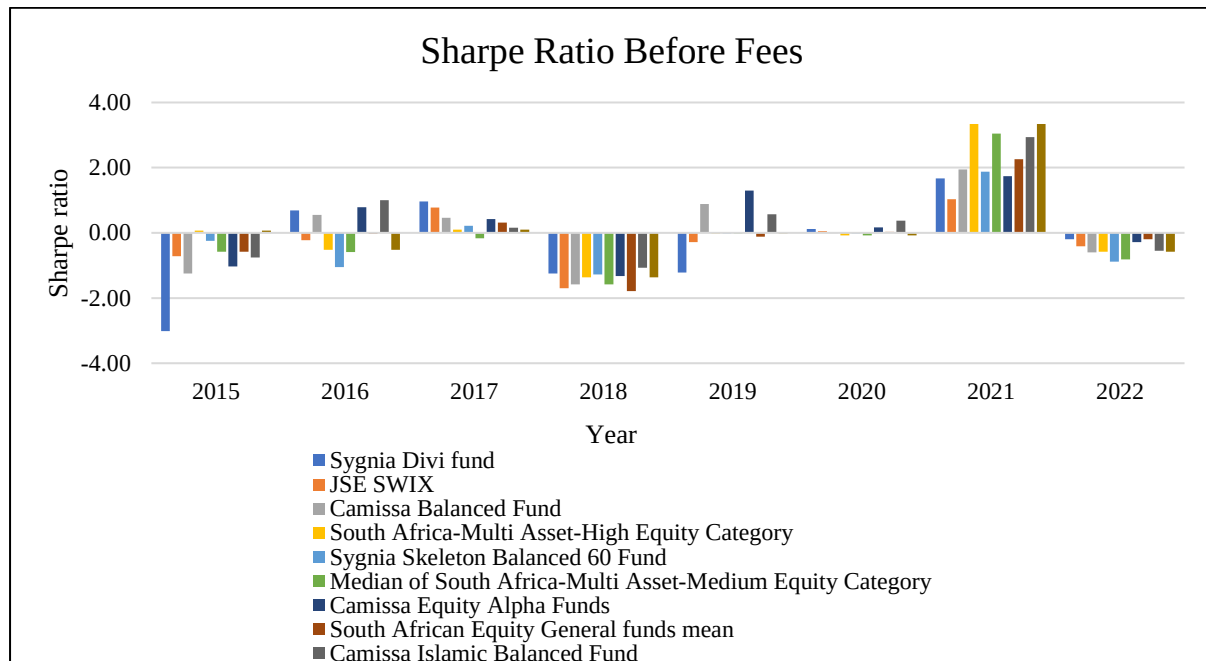


Figure 44 reports the Sharpe ratio results for investors with a moderate tolerance after fees were considered. In 2016, 4 of the 5 portfolios had a positive Sharpe ratio. The years 2017 and 2021 had all portfolios with positive Sharpe ratio. In 2019 and 2020, 3 of the 5 portfolios had a positive Sharpe ratio. 2022 had 1 portfolio with a positive Sharpe ratio. Portfolio performance slightly reduced after fees were considered. However, remains consistent and like the benchmark throughout the years.

Figure 44

Summary of Sharpe ratio for investors with moderate risk tolerance after fees

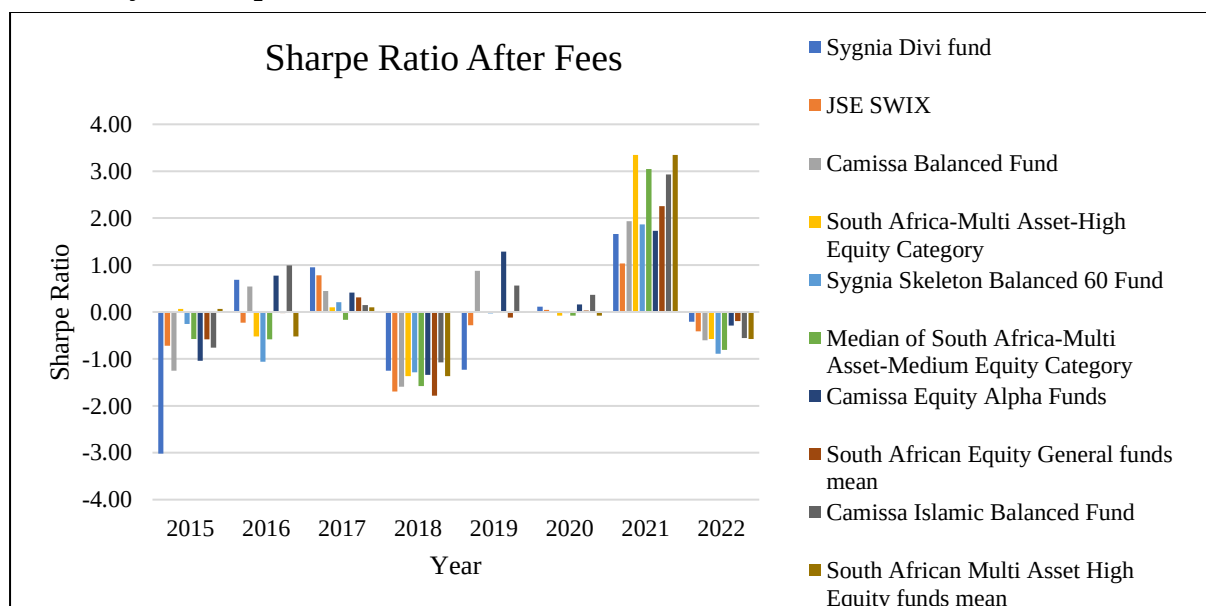


Figure 45 reports the Sharpe ratio results for investors with a low tolerance before fees were considered. All portfolios had a negative Sharpe ratio throughout the years except for in 2020, 2 of the 7 portfolios had a positive Sharpe ratio and 2021 had 1 portfolio with a positive Sharpe ratio. The STeFi composite benchmark had positive Sharpe ratio consistently throughout the years while the portfolios had a negative Sharpe ratio. Portfolio performance remains consistent and like the benchmark throughout the years except for the portfolios that have STeFi composite as a benchmark.

Figure 45

Summary of Sharpe ratio for investors with low risk tolerance before fees

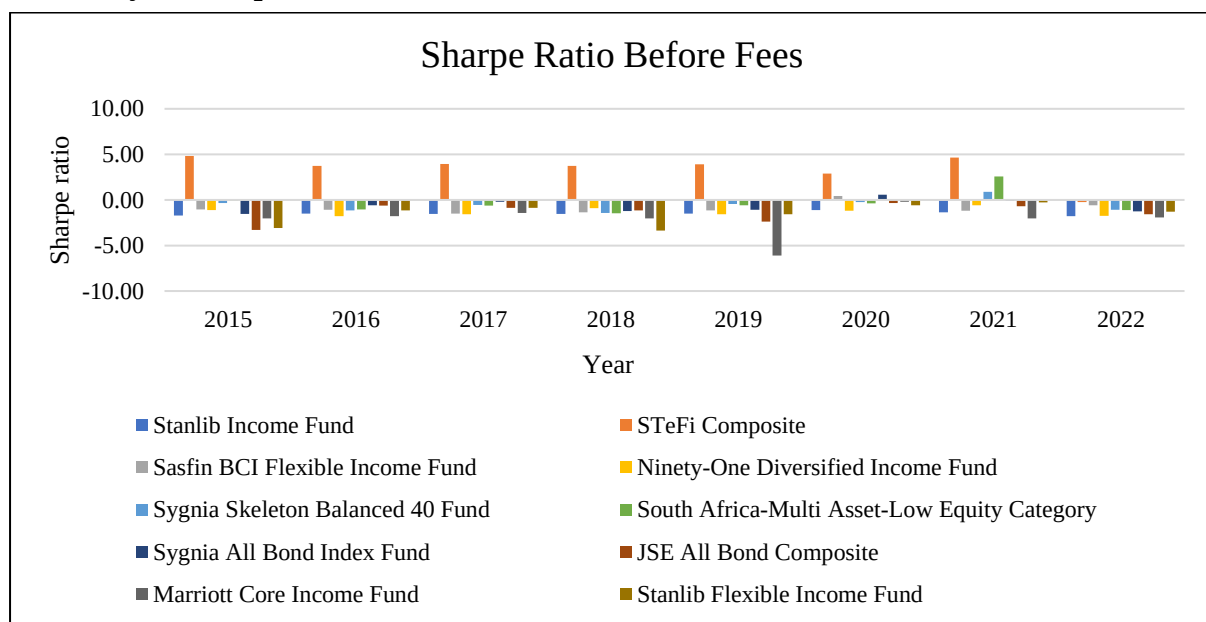
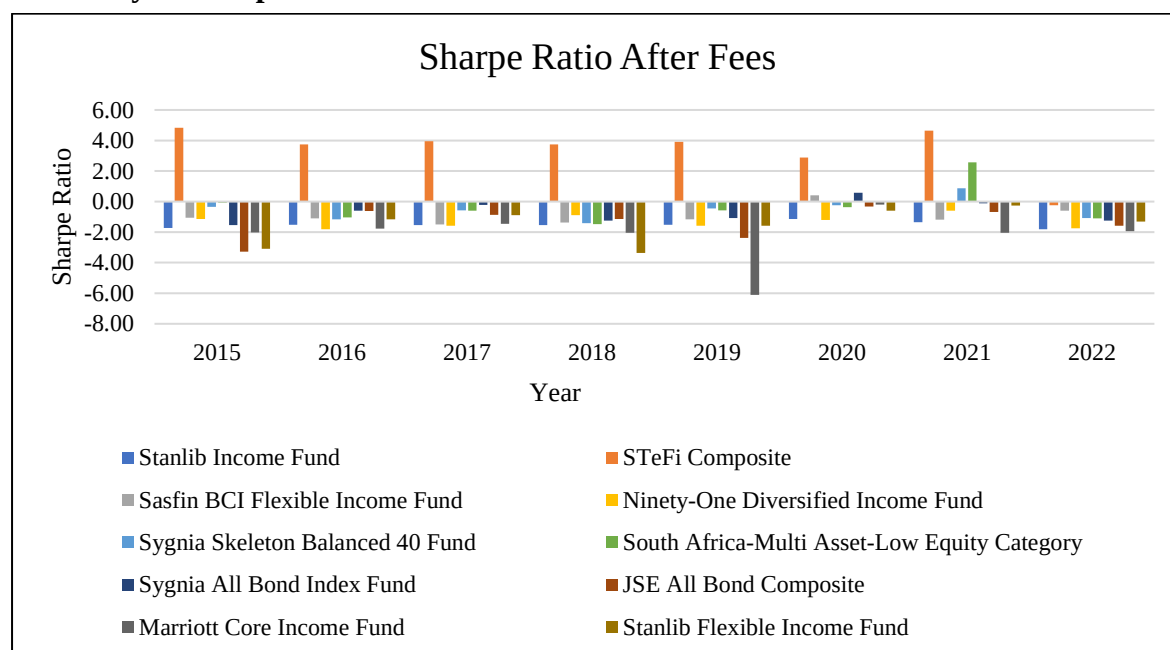


Figure 46 reports the Sharpe ratio results for investors with a low tolerance after fees were considered. All portfolios had a negative Sharpe ratio throughout the years except for in 2020, 2 of the 7 portfolios had a positive Sharpe ratio and 2021 had 1 portfolio with a positive Sharpe ratio. The STeFi composite benchmark had positive Sharpe ratio consistently throughout the years while the portfolios had a negative Sharpe ratio. Portfolio performance slightly reduced after fees were considered but remained consistent and like the benchmark throughout the years except for the portfolios that have STeFi composite as a benchmark.

Figure 46**Summary of Sharpe ratio for investors with low risk tolerance after fees**

4.4.2 Treynor ratio

Figure 47 reports the Treynor ratio results for investors with a high risk tolerance before fees were considered. In 2015, 3 of the 12 portfolios had a positive Treynor ratio. 2016 and 2019 had 4 of the 12 portfolios had a positive Treynor ratio. The years 2017 and 2021 had 11 of the 12 portfolios with positive Treynor ratio. In 2020, 8 of the 12 portfolios had a positive Sharpe 2022 had 1 of the 12 portfolios with positive Sharpe ratios. Portfolio performance remained consistent and like the benchmark throughout the years.

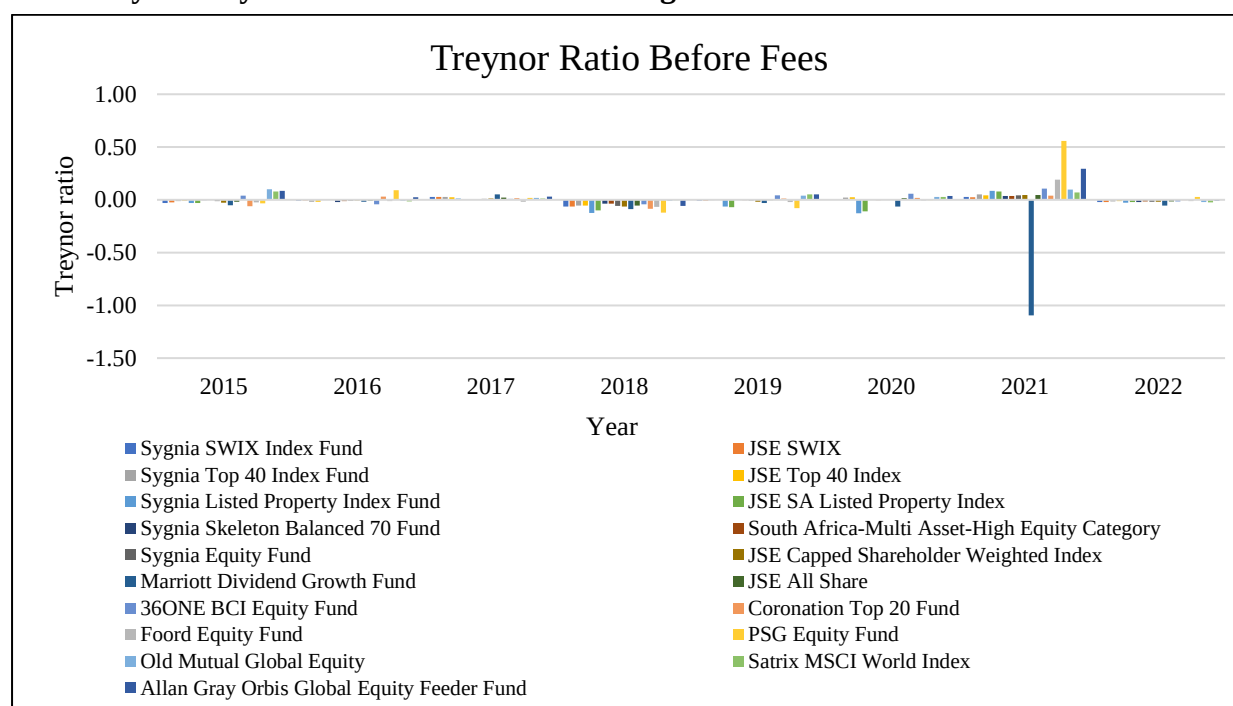
Figure 47**Summary of Treynor ratio for investors with high risk tolerance before fees**

Figure 48 reports the Treynor ratio results for investors with a high tolerance after fees have been considered. In 2015 and 2016, 3 of the 12 portfolios had a positive Treynor ratio. 2019 had 4 of the 12 portfolios had a positive Treynor ratio. The years 2017 and 2021 had 11 of the 12 portfolios with positive Treynor ratio. In 2020, 8 of the 12 portfolios had a positive Sharpe 2022 had 1 of the 12 portfolios with positive Sharpe ratios. Portfolio performance remained consistent and like the benchmark throughout the years.

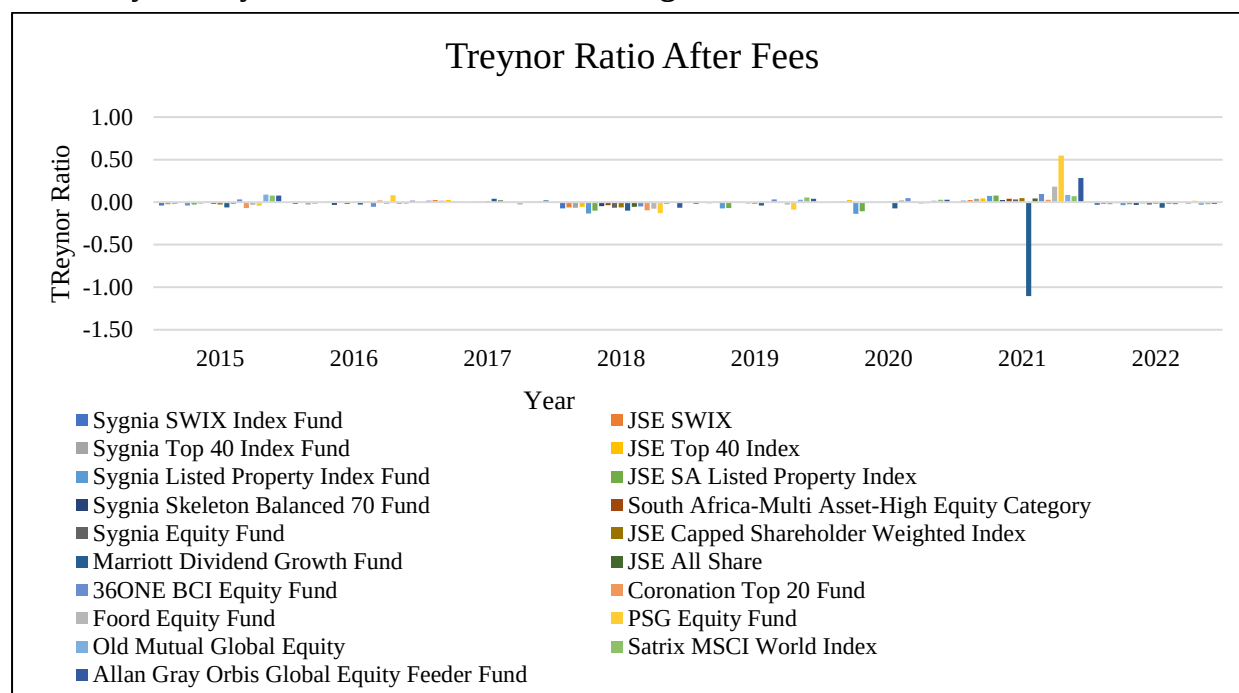
Figure 48**Summary of Treynor ratio for investors with high risk tolerance after fees**

Figure 49 reports the Treynor ratio results for investors with a moderate risk tolerance before fees were considered. In 2016, 4 of the 5 portfolios had a positive Treynor ratio. 2019 had 3 of the 5 portfolios had a positive Treynor ratio. The years 2017 and 2021 had all portfolios with positive Treynor ratio. In 2020, 1 of the 5 portfolios had a positive Treynor ratio. Portfolio performance remained consistent and like the benchmark throughout the years.

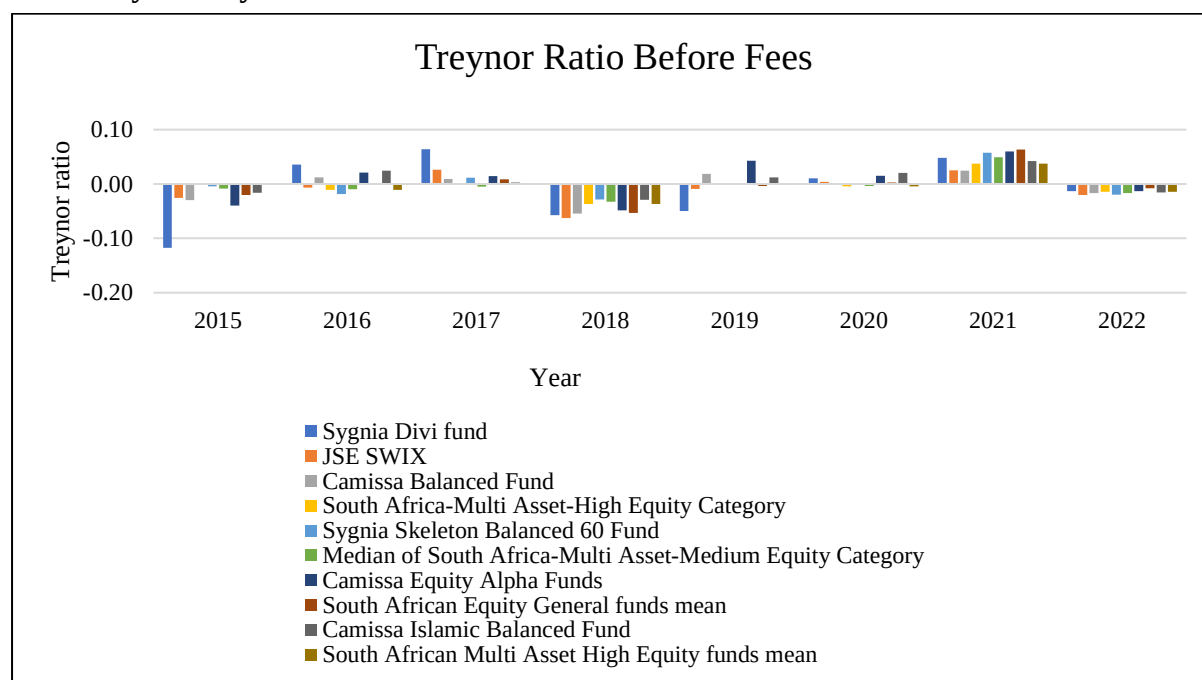
Figure 49**Summary of Treynor ratio for investors with moderate risk tolerance before fees**

Figure 50 reports the Treynor ratio results for investors with a moderate risk tolerance after fees have been considered. In 2016, 4 of the 5 portfolios had a positive Treynor ratio. 2017, 2019 and 2020 had 3 of the 5 portfolios had a positive Treynor ratio. The year 2021 had all portfolios with positive Treynor ratio. Portfolio performance slightly reduced after fees were considered.

Figure 50

Summary of Treynor ratio for investors with moderate risk tolerance after fees

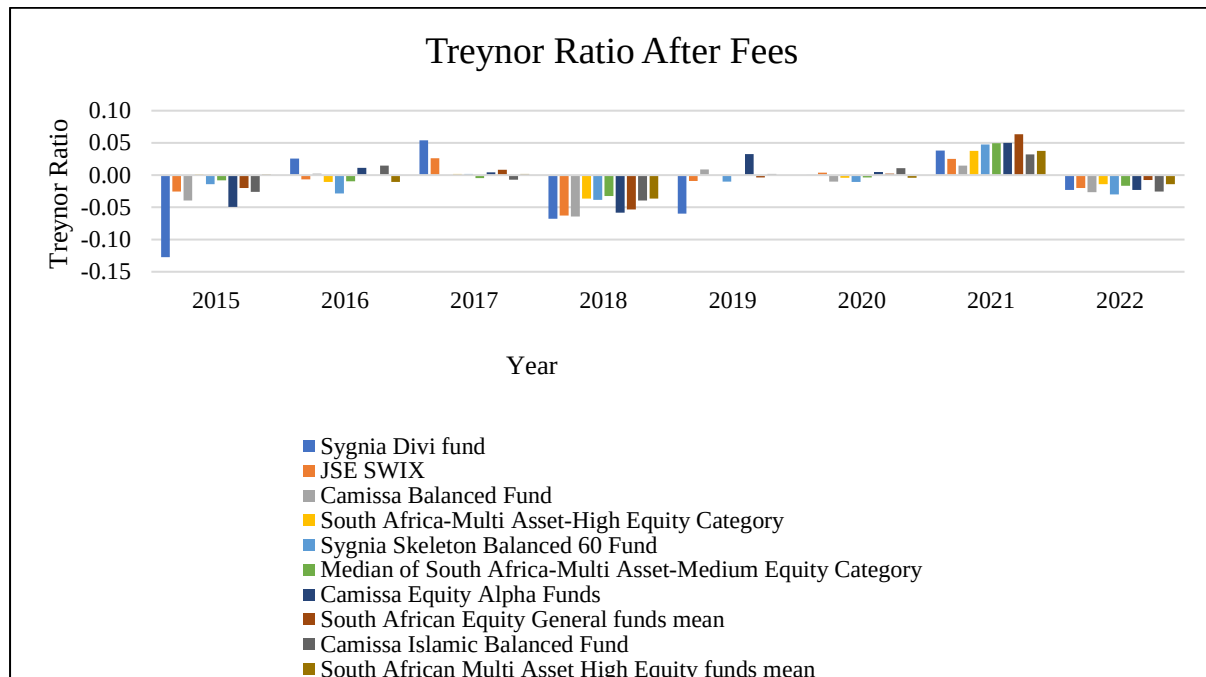


Figure 51 reports the Treynor ratio results for investors with a low risk tolerance before fees are considered. In 2016, 4 of the 5 portfolios had a positive Treynor ratio. 2017 and 2021 had all portfolios that had a positive Treynor ratio. The years 2019 and 2020 had 3 of the 5 portfolios with positive Treynor ratio. Portfolio performance remained consistent and like the benchmark throughout the years.

Figure 51

Summary of Treynor ratio for investors with low risk tolerance before fees

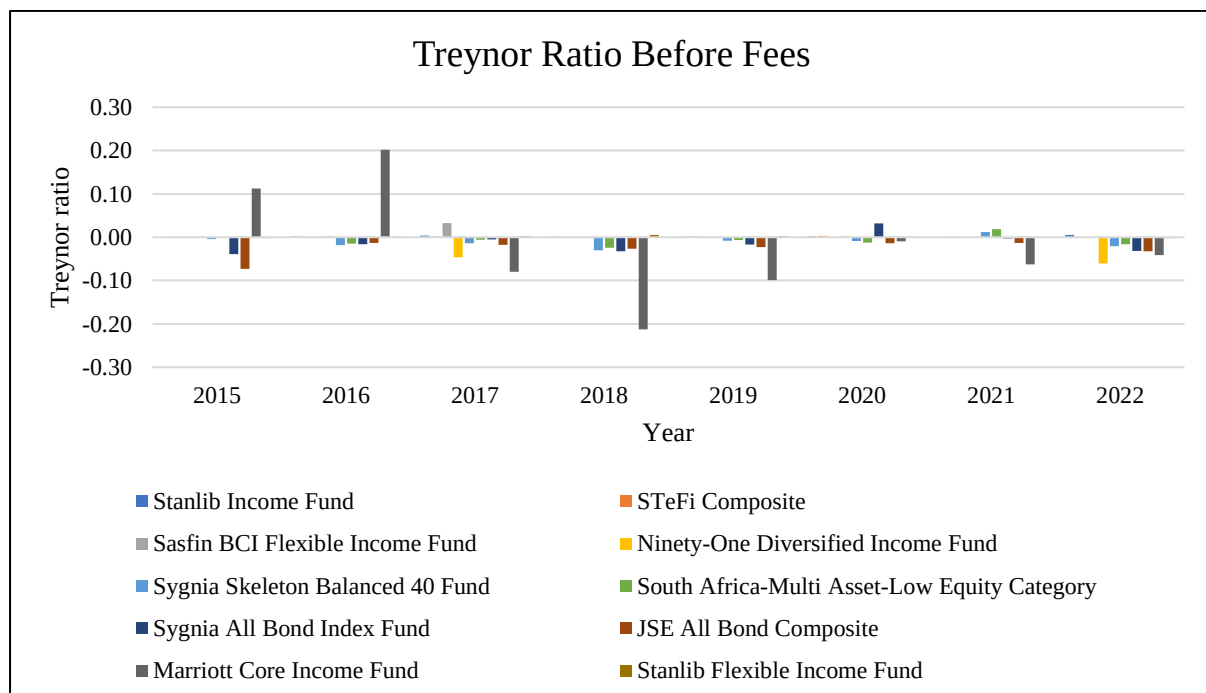
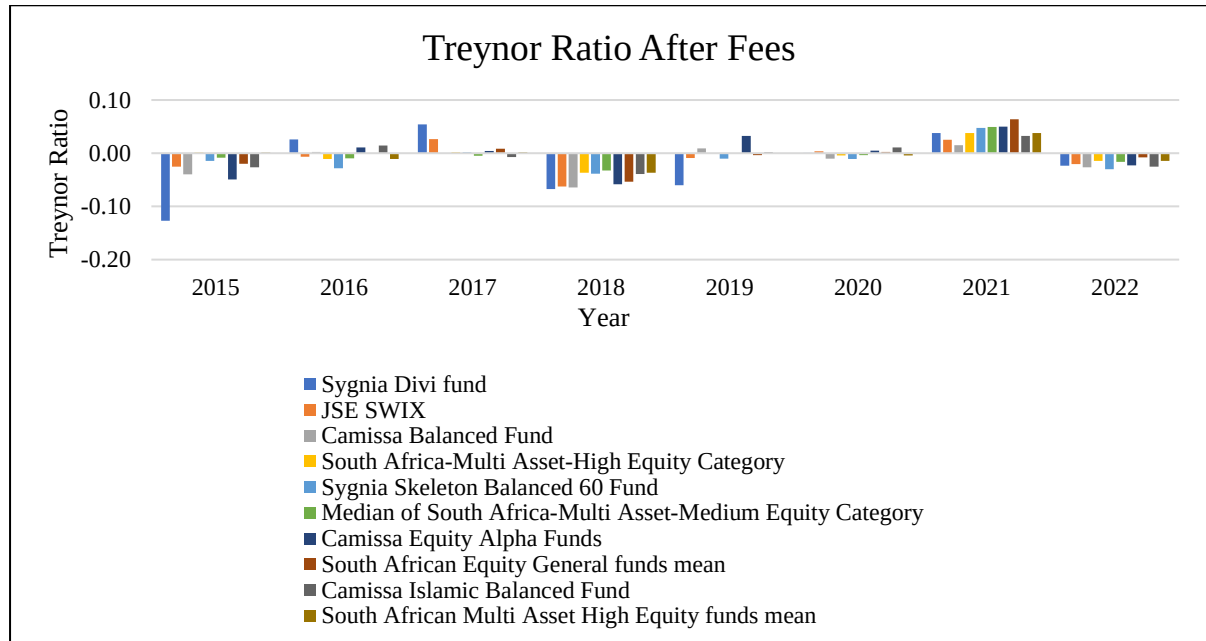


Figure 52 reports the Treynor ratio results for investors with a low risk tolerance after fees are considered. In 2015, 2016, 2017, 2020 and 2021 had 1 of the 5 portfolios had a positive Treynor ratio. Portfolio performance reduced slightly once fees were considered.

Figure 52

Summary of Treynor ratio for investors with low risk tolerance after fees



4.4.3 Jensen's alpha

Figure 53 reports the Jensen's alpha results for investors with a high risk tolerance before fees were considered. In 2015, 2016 and 2020, 6 of the 12 portfolios had a positive alpha. 2017 had 7 of the 12 portfolios had a positive alpha. The years 2018 had 2 of the 12 portfolios with positive alpha ratio. In 2019, 5 of the 12 portfolios had a positive alpha. 2021 had 10 of the 12 portfolios with positive alpha and 2022 had 7 of the 12 portfolios had a positive alpha.

Figure 53

Summary of Jensen's alpha for investors with high tolerance before fees

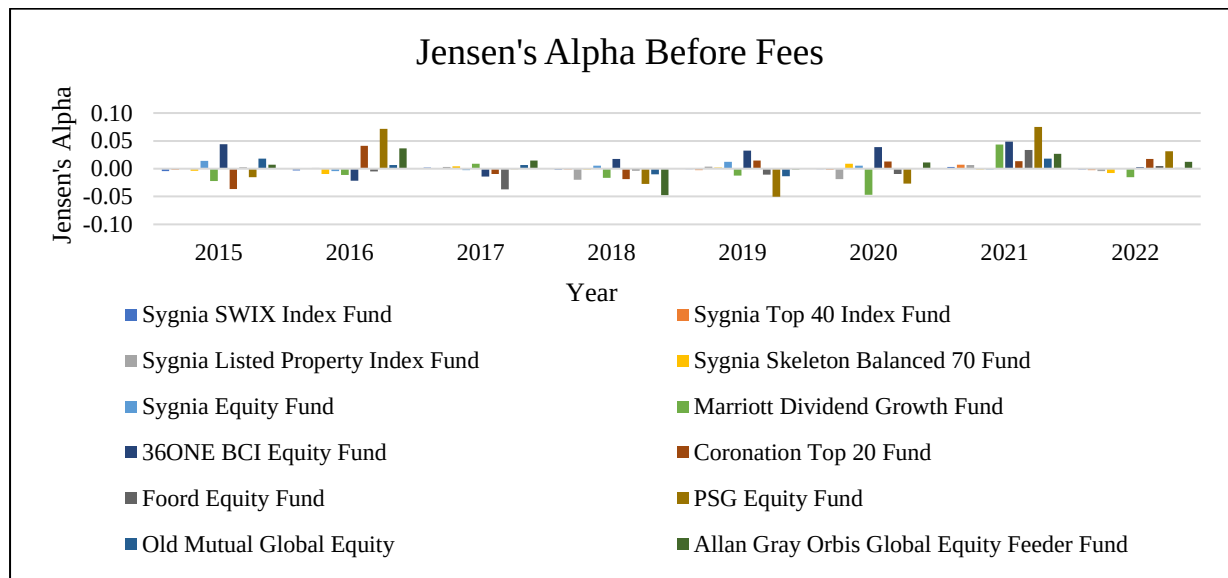


Figure 54 reports the Jensen's alpha results for investors with a high risk tolerance after fees were considered. In 2015, 2016, 2019, 2020 and 2022, 3 of the 12 portfolios had a positive alpha. 2017 and 2018 had 1 of the 12 portfolios had a positive alpha. The years 2021 had 2 of the 12 portfolios with positive alpha ratio. In 2019, 5 of the 12 portfolios had a positive alpha. 2021 had 7 of the 12 portfolios with positive alpha. Portfolio performance reduced once fees were considered.

Figure 54

Summary of Jensen's alpha for investors with high tolerance after fees

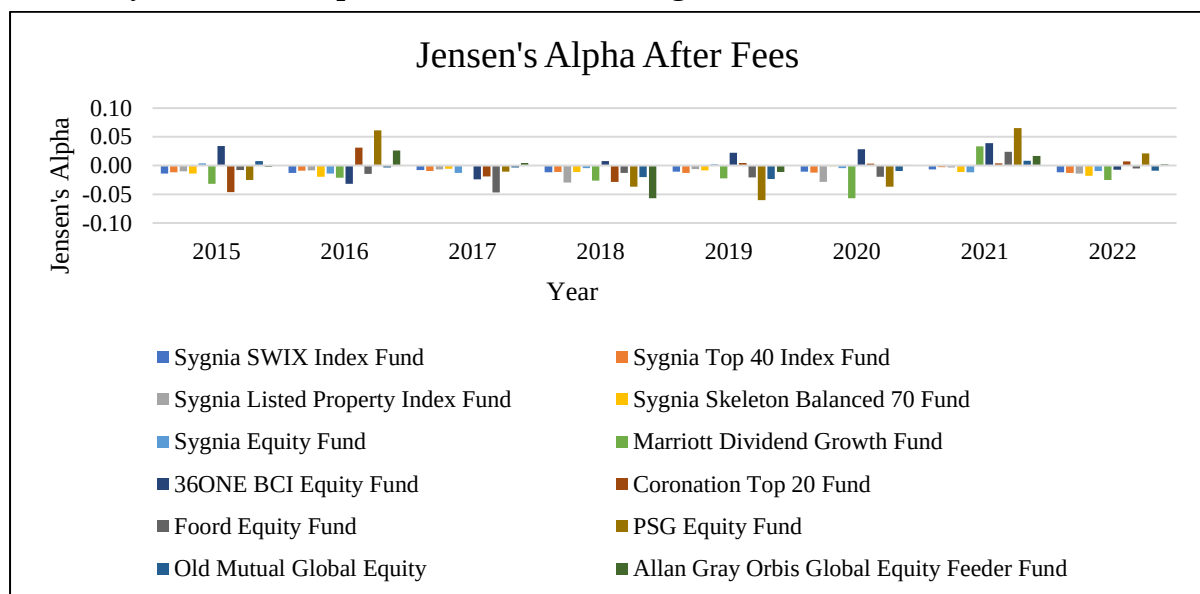


Figure 55 reports the Jensen's alpha results for investors with a moderate tolerance before fees were considered. In 2015 and 2022, 1 of the 5 portfolios had a positive alpha. In 2016 and 2018, 4 of the 5 portfolios had a positive alpha. 2017 and 2020 portfolios all had a positive alpha. In 2019 and 2021, 3 of the 5 portfolios had a positive alpha. 2020 had 2 of the 5 portfolios with positive alpha.

Figure 55

Summary of Jensen's alpha for investors with moderate risk tolerance before fees

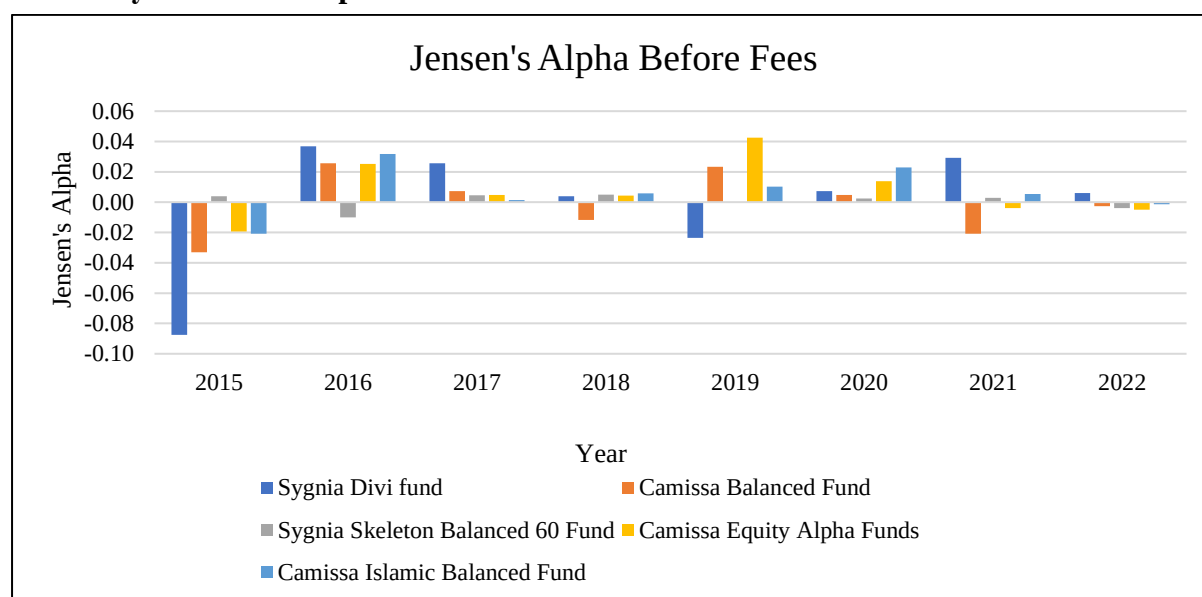


Figure 56 reports the Jensen's alpha results for investors with a moderate tolerance before fees were considered. In 2016, 4 of the 5 portfolios had a positive alpha. 2017 and 2021 had 1 of the 5 portfolios had a positive alpha. In 2019, 3 of the 5 portfolios had a positive alpha. 2020 had 2 of the 5 portfolios with positive alpha. Portfolio performance reduced once fees were considered.

Figure 56

Summary of Jensen's alpha for investors with moderate risk tolerance before fees

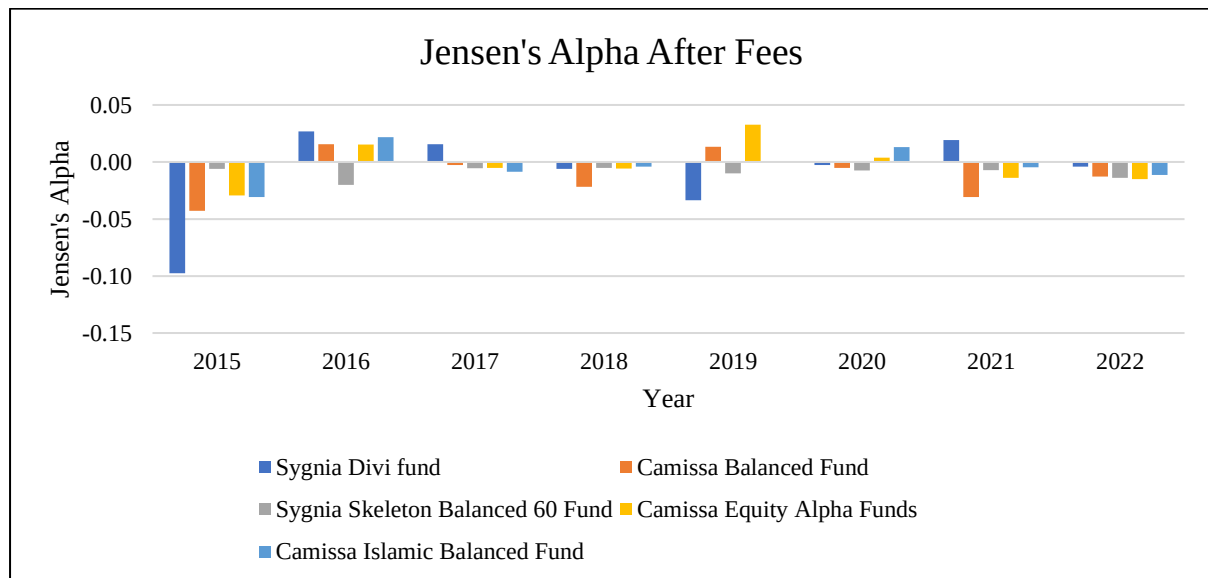


Figure 57 reports the Jensen's alpha results for investors with a low risk tolerance before fees are considered. In 2015 and 2016, 2 of the 7 portfolios had a positive alpha. 2017, 2021 and 2022 had 1 of the 7 portfolios had a positive alpha. In 2018, 3 of the 7 portfolios had a positive alpha. 2019 had 4 of the 7 portfolios with positive alpha. 2020 portfolios all had positive alpha.

Figure 57

Summary of Jensen's alpha for investors with low tolerance before fees

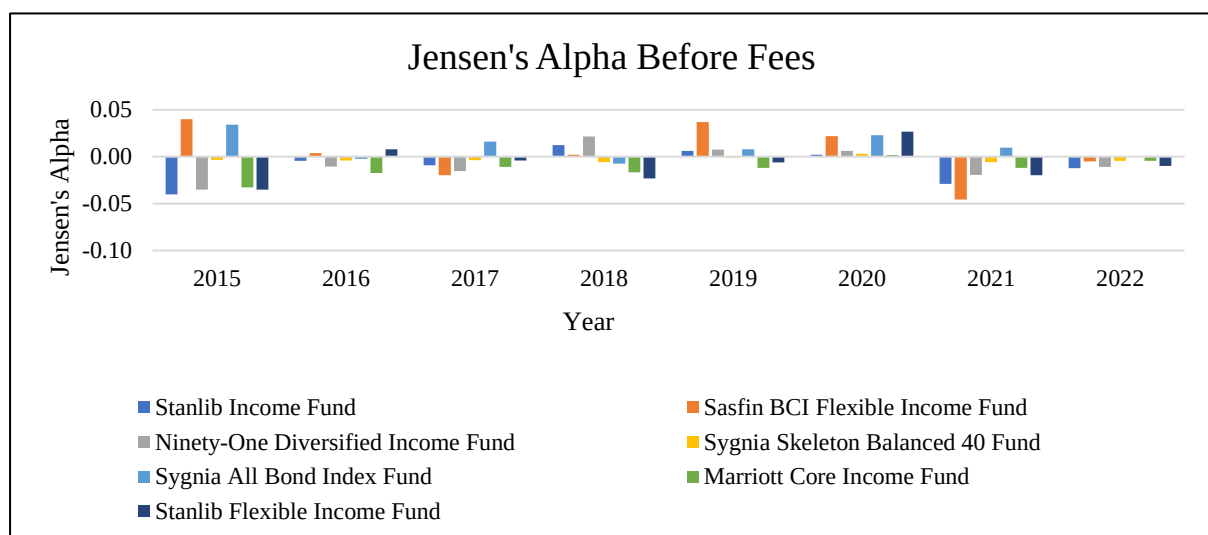
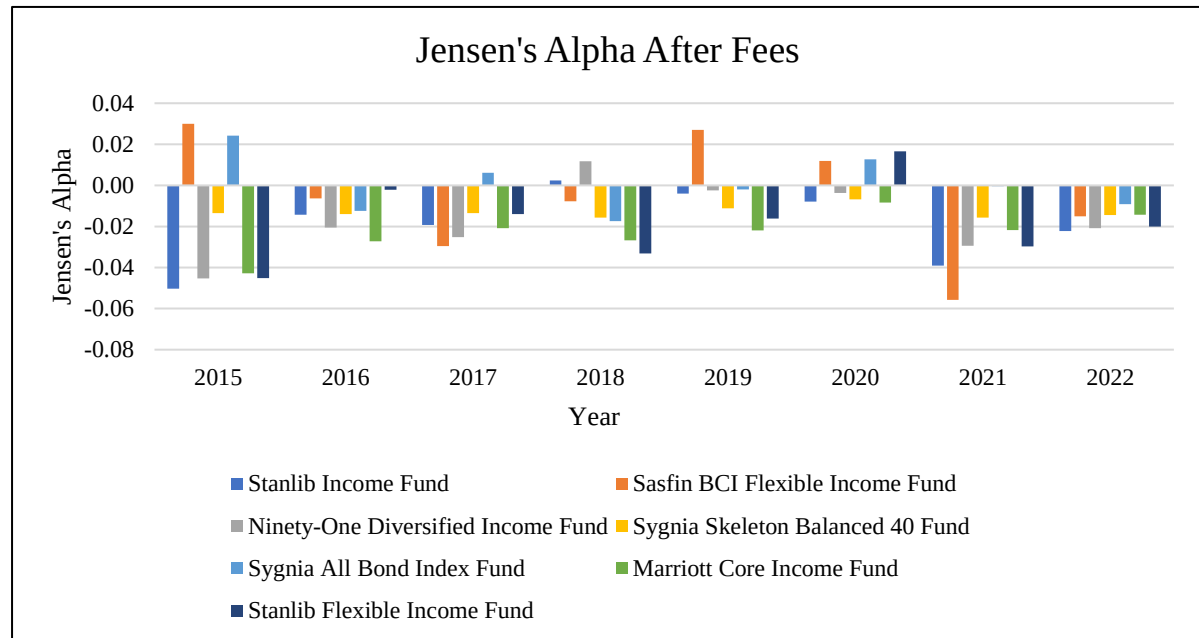


Figure 58 reports the Jensen's alpha results for investors with a low risk tolerance after fees are considered. In 2015 and 2018, 2 of the 7 portfolios had a positive alpha. 2017 and 2019 had

1 of the 7 portfolios had a positive alpha. Portfolio performance reduced once fees were considered.

Figure 58

Summary of Jensen's alpha for investors with low tolerance after fees



4.4.4 Manipulation-proof performance measure

Figure 59 reports the MPPM results for investors with a high tolerance before fees are considered and **Figure 60** reports the MPPM results with a high tolerance after fees were considered. The results showed that the MPPM is positive for all portfolios. The MPPM remains the same for both before and after fees.

Figure 59

Summary of manipulation-proof performance measure for investors with high tolerance before fees

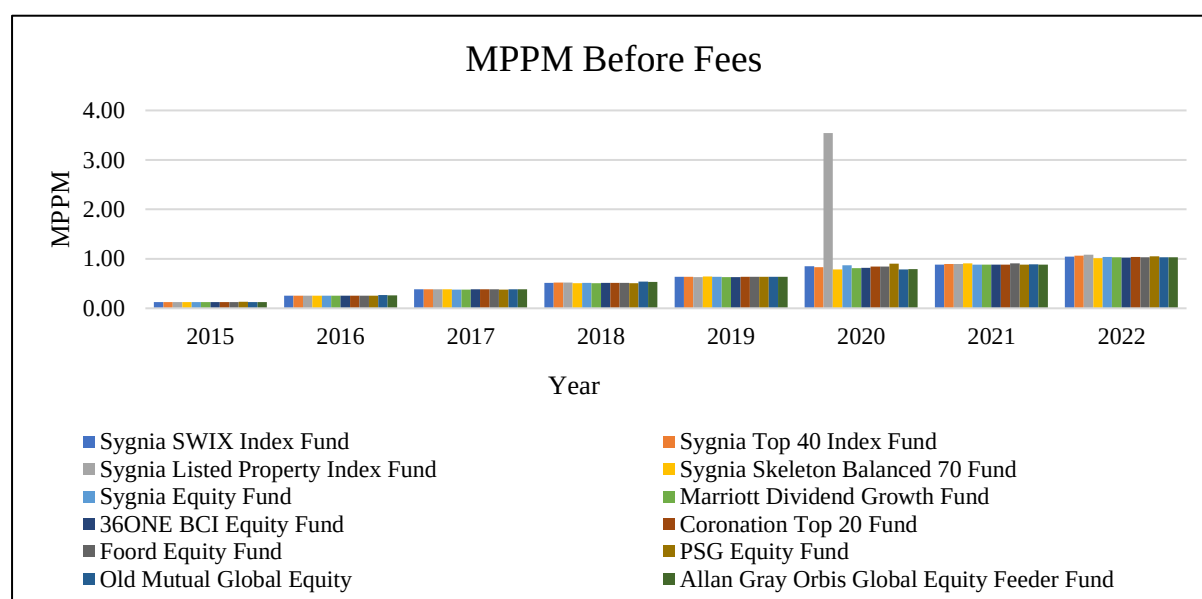


Figure 60

Summary of manipulation-proof performance measure for investors with high tolerance after fees

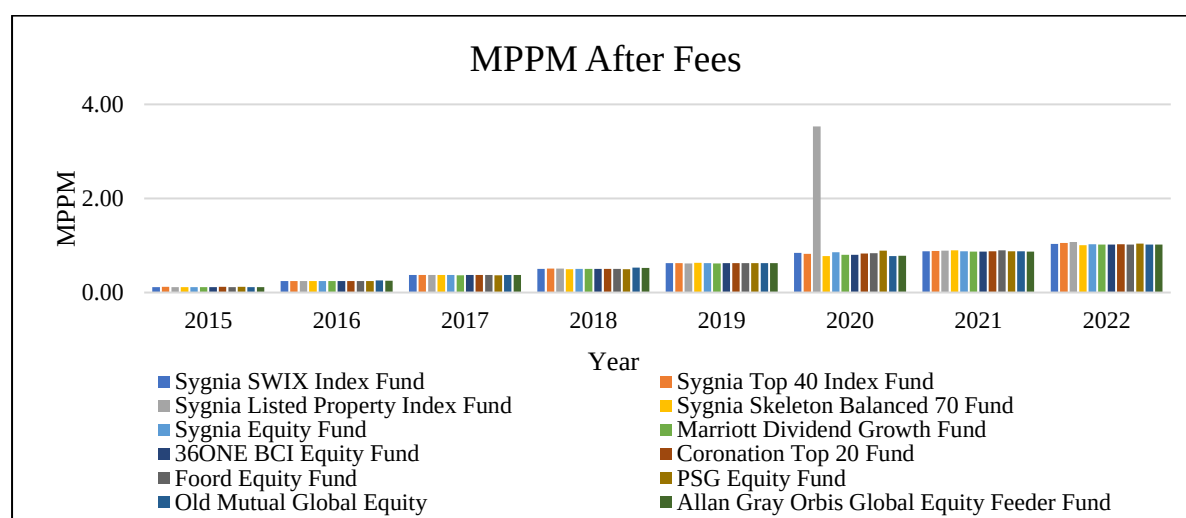


Figure 61 reports the MPPM results for investors with a moderate tolerance before fees are considered and **Figure 62** reports the MPPM results with a moderate tolerance after fees were considered. The results showed that the MPPM is positive for all portfolios. The MPPM remains the same for both before and after fees.

Figure 61

Summary of manipulation proof performance measure for investors with moderate risk tolerance before fees

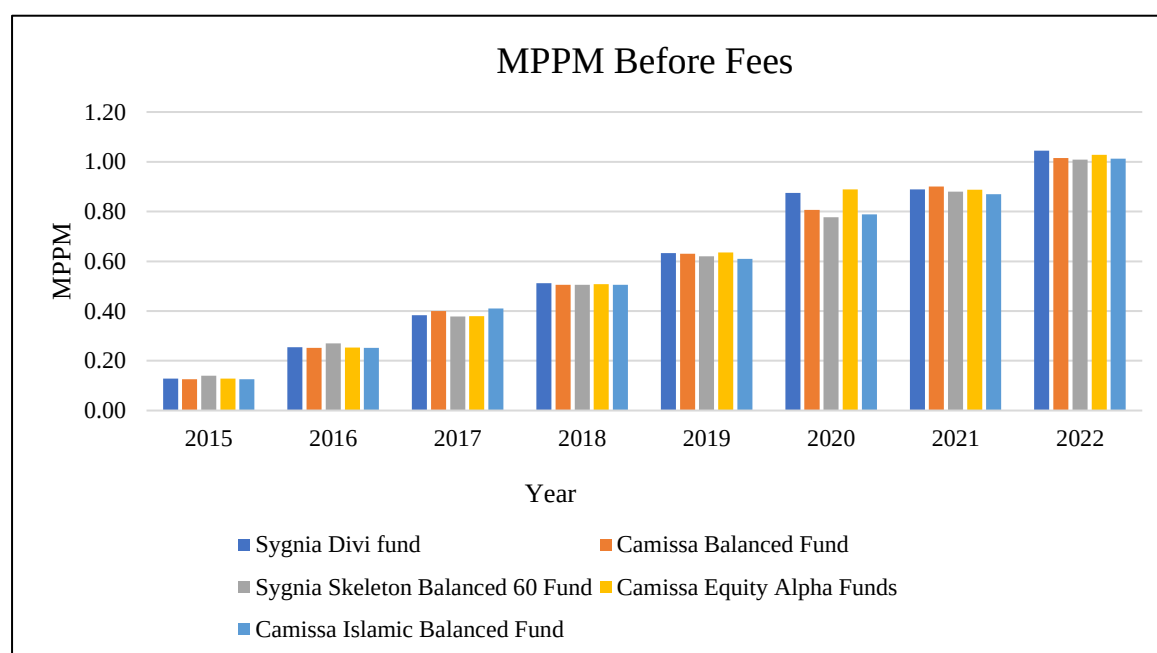


Figure 62

Summary of manipulation proof performance measure for investors with moderate risk tolerance after fees

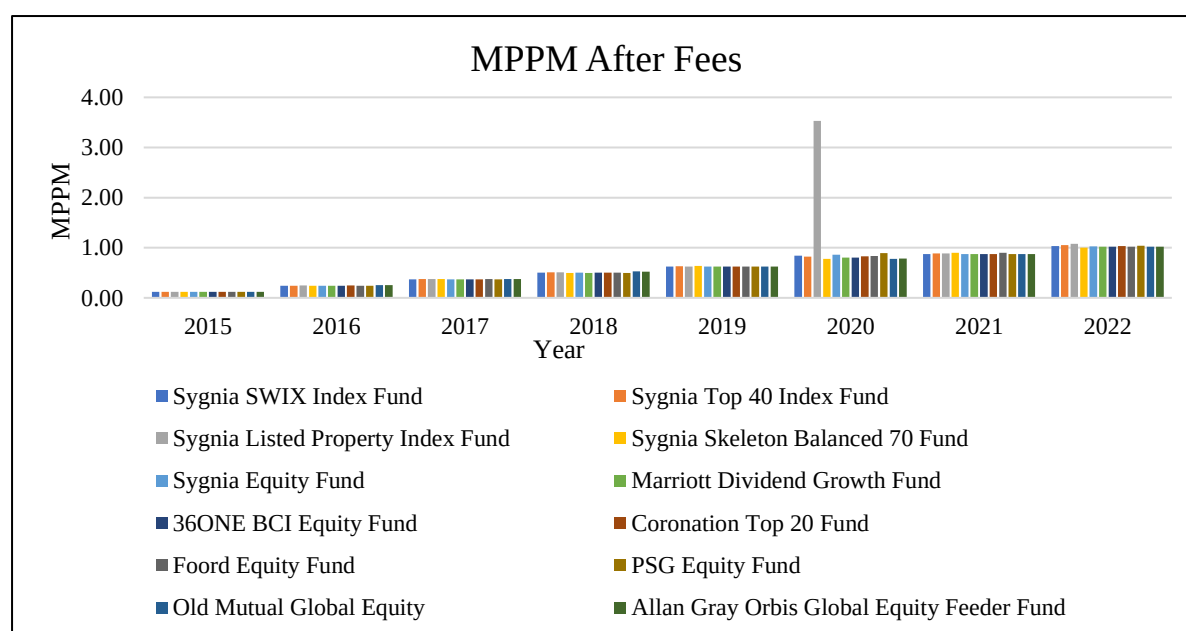


Figure 63 reports the MPPM results for investors with a moderate tolerance before fees are considered and **Figure 64** reports the MPPM results with a moderate tolerance after fees were considered. The results showed that the MPPM is positive for all portfolios. The MPPM remains the same for both before and after fees.

Figure 63

Summary of manipulation-proof performance measure for investors with low tolerance before fees

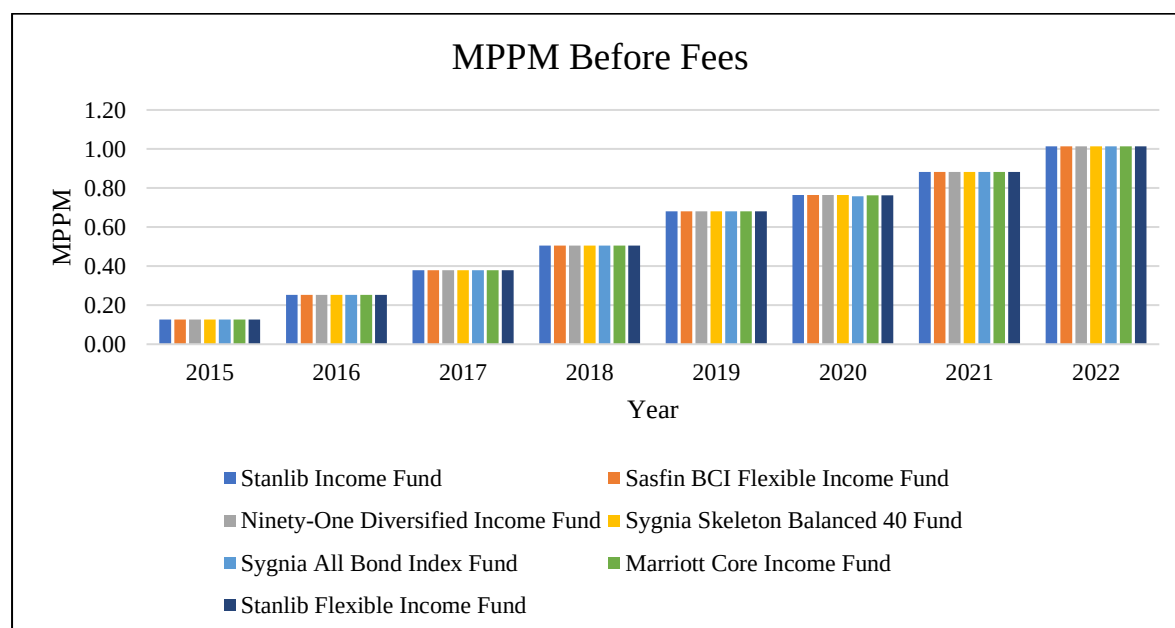
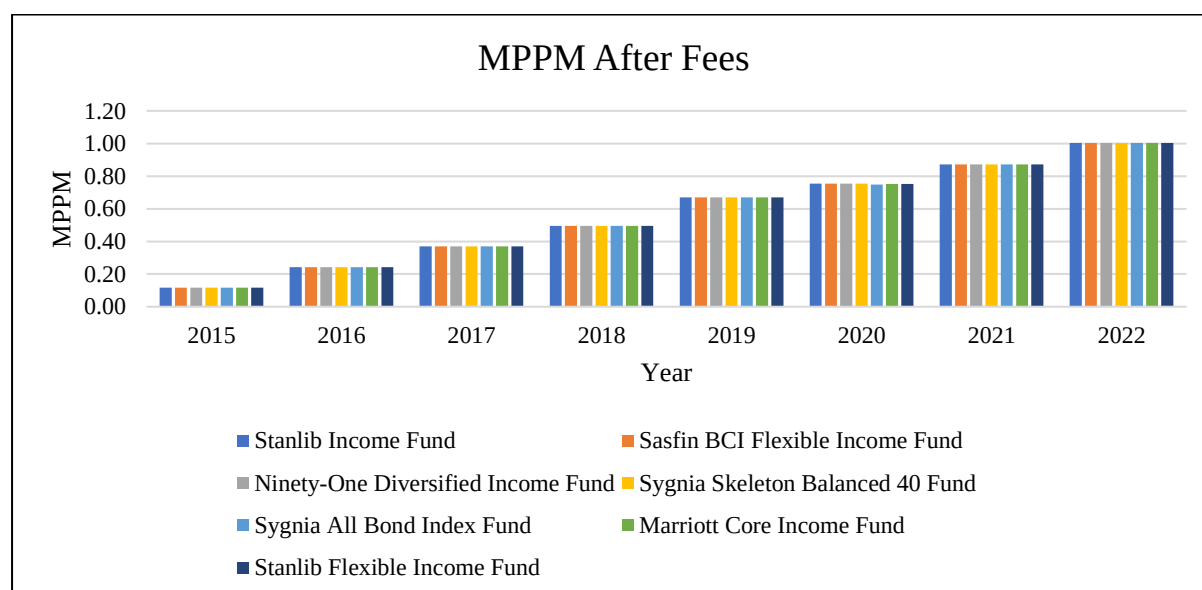


Figure 64

Summary of manipulation-proof performance measure for investors with low tolerance after fees



4.5 Asset allocation

To analyse the exposure of the typical asset allocation, three asset classes were looked at namely developed and emerging markets equity, real estate, government, and corporate bonds.

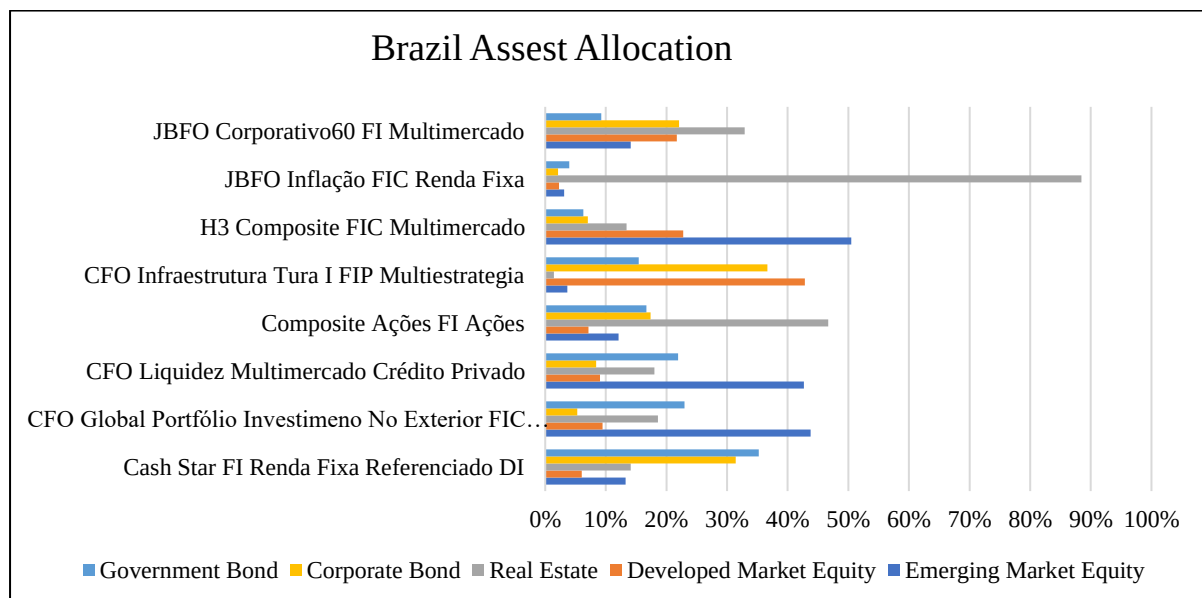
This was to determine the exposure of the different portfolios recommended by robo advisors to uncorrelated assets using a return-based style analysis to provide additional insight on the returns i.e. the source of the returns on the robo advisor recommended by the robo advisor. Additionally, the portfolios are assessed to determine if the portfolios have similar investment styles. This was to explain the performance differences between the portfolios.

4.5.1 Brazil

To provide additional insight into the source of the portfolio returns, a constrained regression was conducted. **Figure 65** is a summary of the estimated asset allocation for Brazil. The results showed that most of the assets for the portfolios recommended by the robo advisor in Brazil were mostly in the emerging market equity, real estate, and government bonds.

Figure 65

Summary of the estimated asset allocation for Brazil



4.5.2 India

Figure 66 is a summary of the estimated asset allocation for India. The results showed that many of the assets for the portfolios recommended by the robo advisor in India were mostly in the developed market equity and government bonds.

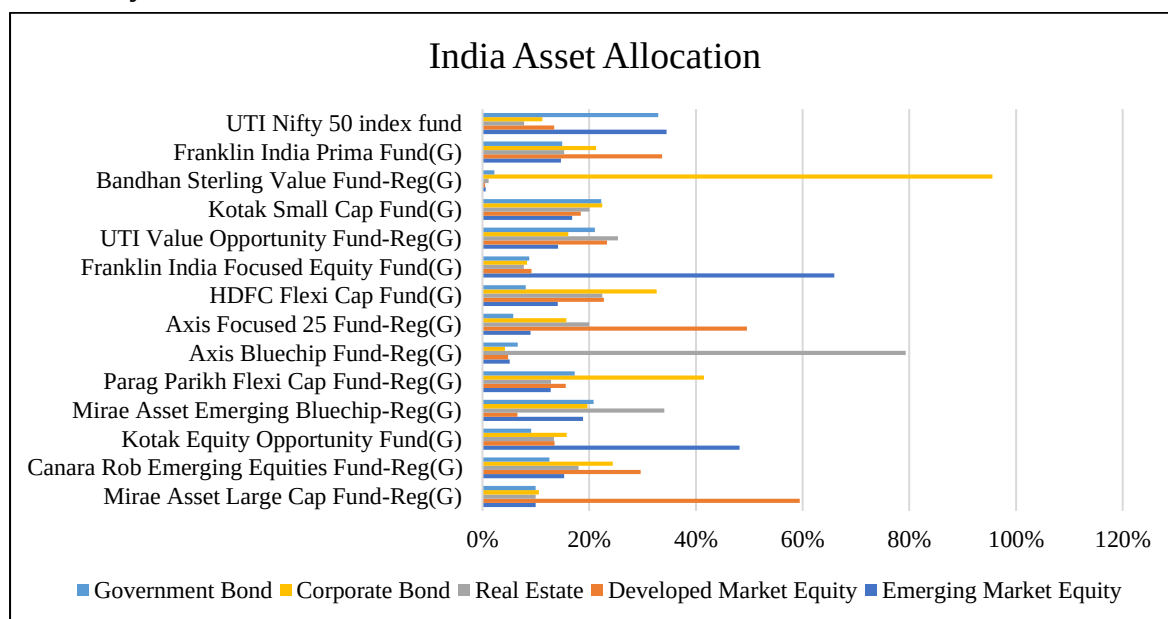
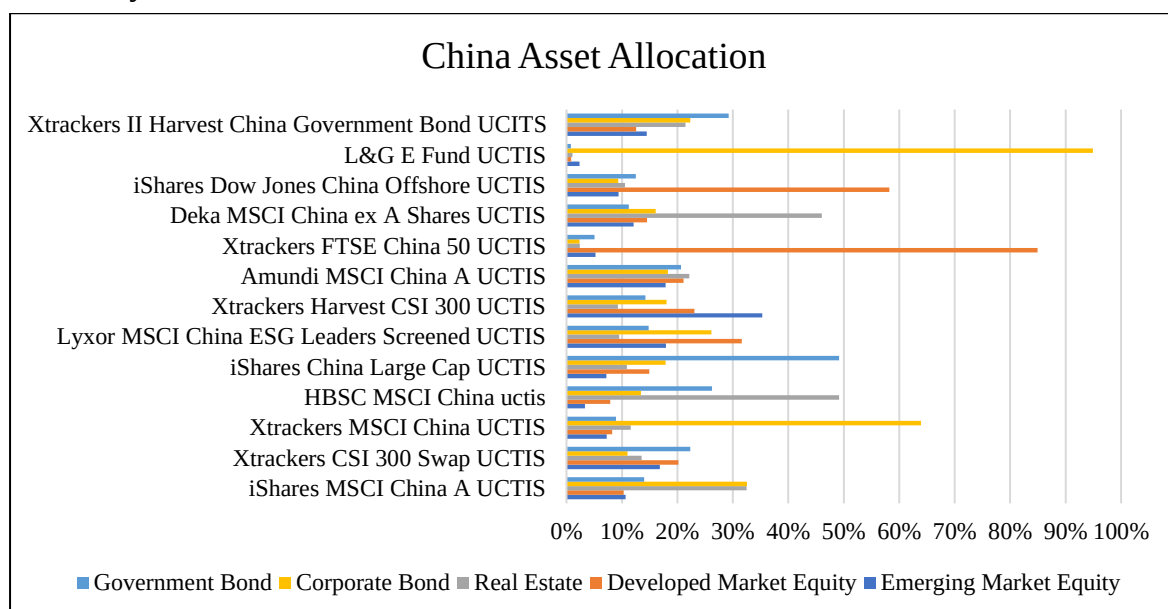
Figure 66**Summary of the estimated asset allocation for India****4.5.3 China**

Figure 67 is a summary of the estimated asset allocation for China. The results showed that most of the assets for the portfolios recommended by the robo advisor in China were mostly in the developed market equity and real estate.

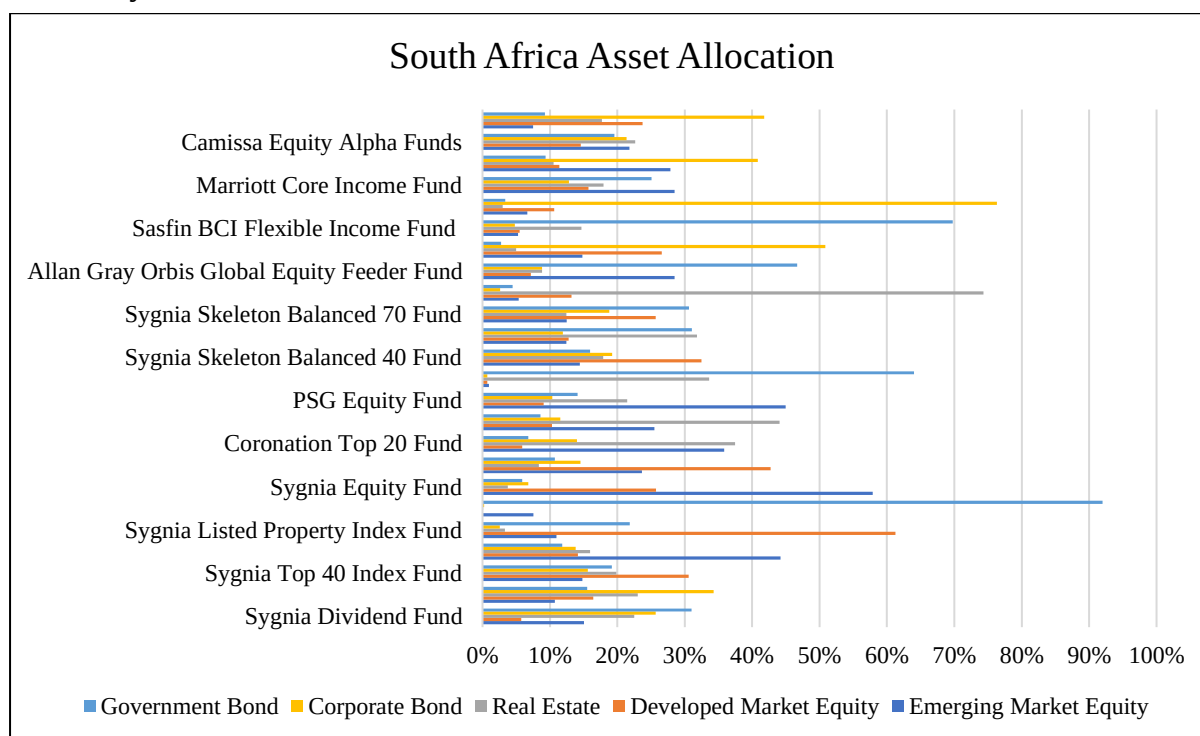
Figure 67**Summary of the estimated asset allocation for China**

4.5.4 South Africa

Figure 68 is a summary of the estimated asset allocation for South Africa. The results showed that most of the assets for the portfolios recommended by the robo advisor in South Africa were mostly in the developed and emerging market equities, and government bonds

Figure 68

Summary of estimated asset allocation for South Africa



4.6 Common style analysis

To determine if there were similar investment styles between the portfolios of the different robo advisors, a common style analysis is conducted. This was done to provide any explanation on the performance differences between the different portfolios of the different robo advisors in BRICS countries. The results of the common style analysis will be provided in this section.

Figure 69 reports on the summary of the common style percentage between South African and Brazilian portfolios for investors with a high-risk tolerance. The highest common style percentage was between Sygnia Listed Property Index Fund and CFO Infraestrutura Tura I FIP Multiestrategia (77.30%).

Figure 69

Common style percentage between South African and Brazilian portfolios for high risk investors

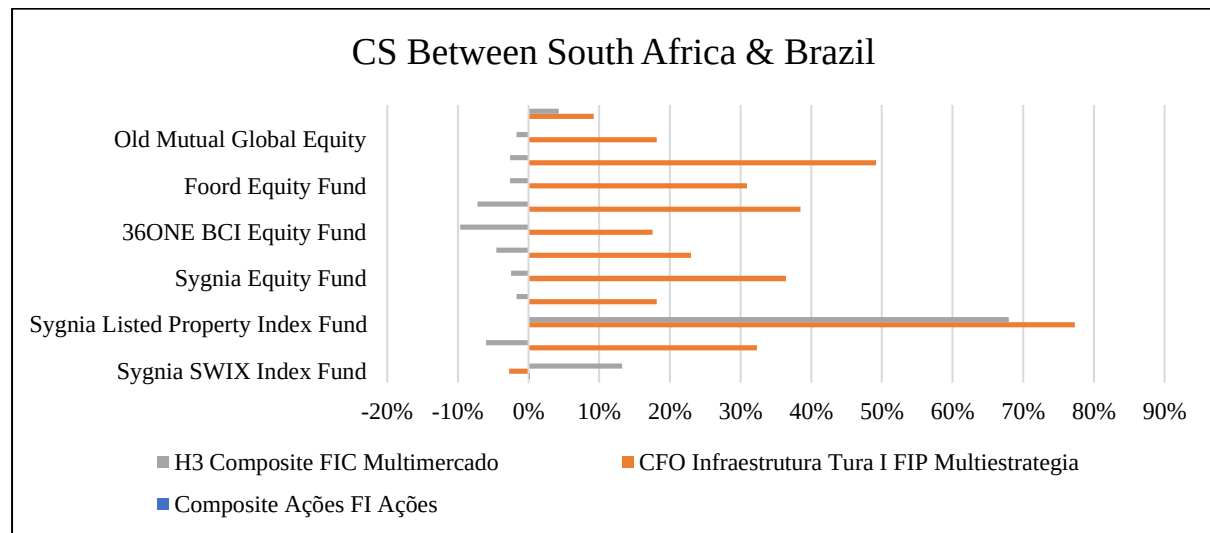


Figure 70 reports on the summary of the common style percentage between South African and Indian portfolios for investors with a high-risk tolerance. The highest common style percentage was between Parag Parikh Flexi Cap Fund and Allan Gray Orbis Global Equity Feeder Fund (99.10%).

Figure 70

Common style percentage between South African and Indian portfolios for high risk investors

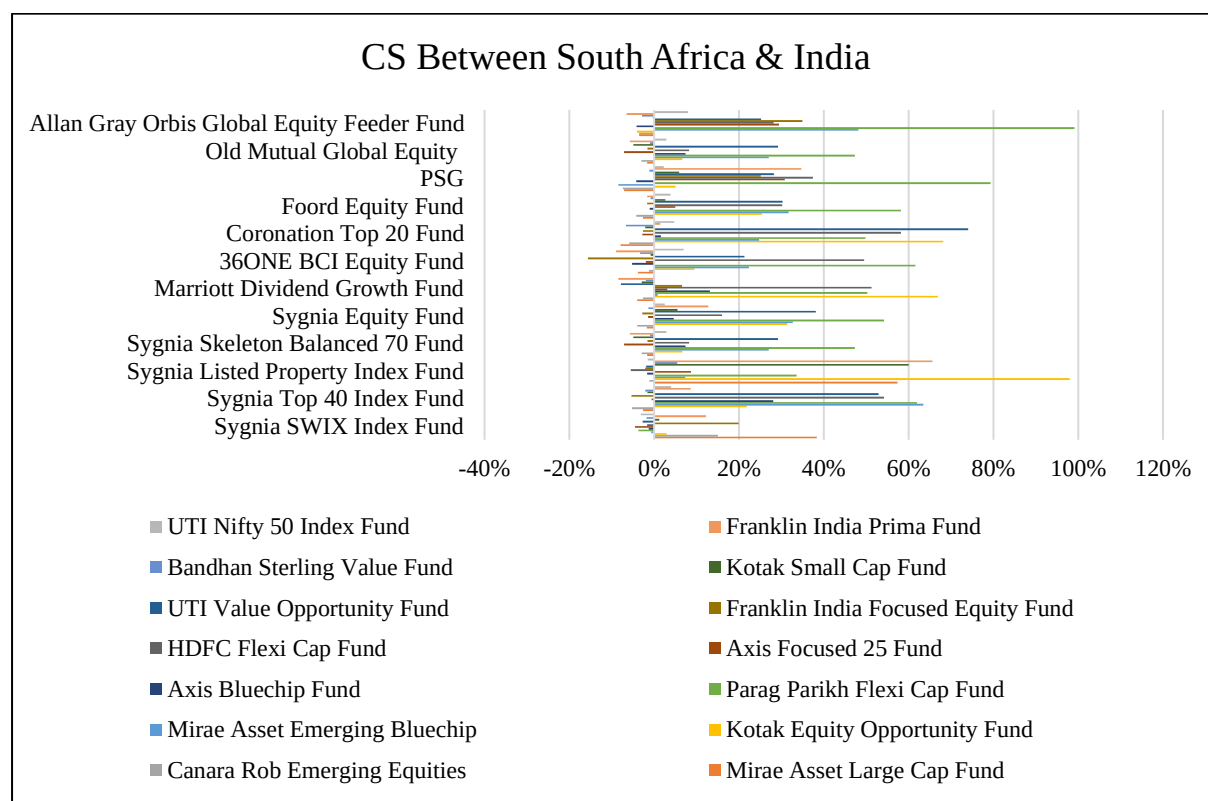


Figure 71 reports on the summary of the common style percentage between South African and Chinese portfolios for investors with a high-risk tolerance. The highest common style percentage was between Sygnia Listed Property Index Fund and Xtrackers MSCI China UCTIS (88.78%).

Figure 71

Common style percentage between South African and Chinese portfolios for high risk

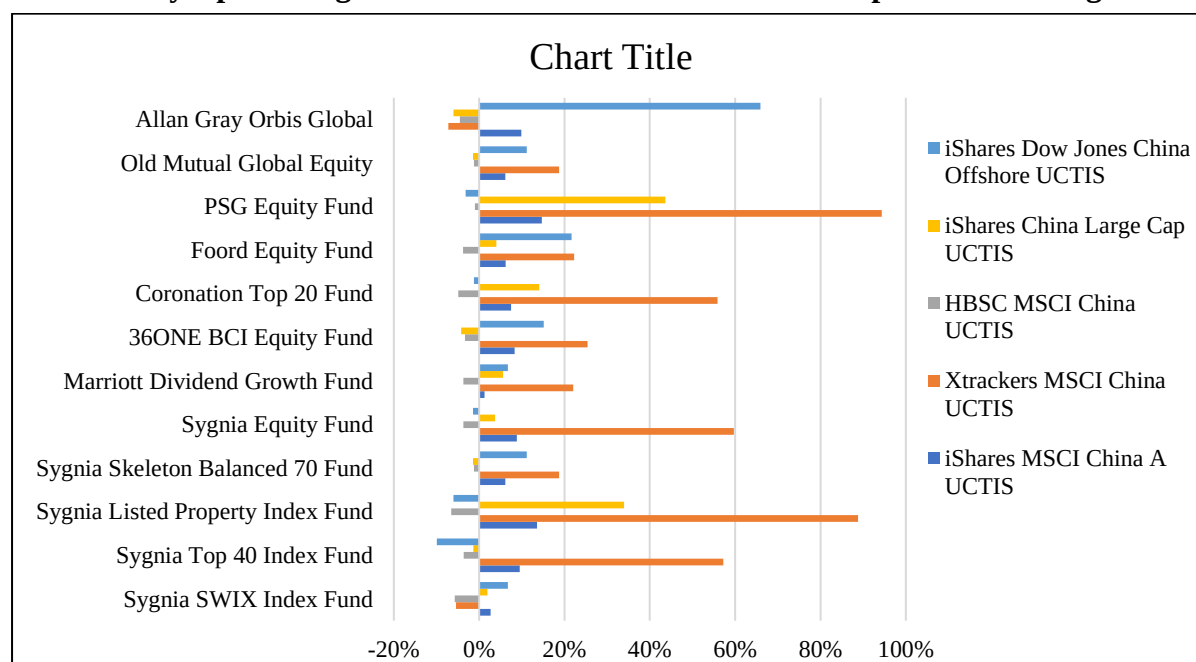


Figure 72 reports on the summary of the common style percentage between South African and Chinese portfolios for investors with a high risk tolerance. The highest common style percentage was between Sygnia Listed Property Index Fund and Xtrackers MSCI China UCTIS (88.78%).

Figure 72

Common style percentage between South African and Brazilian portfolios for high risk

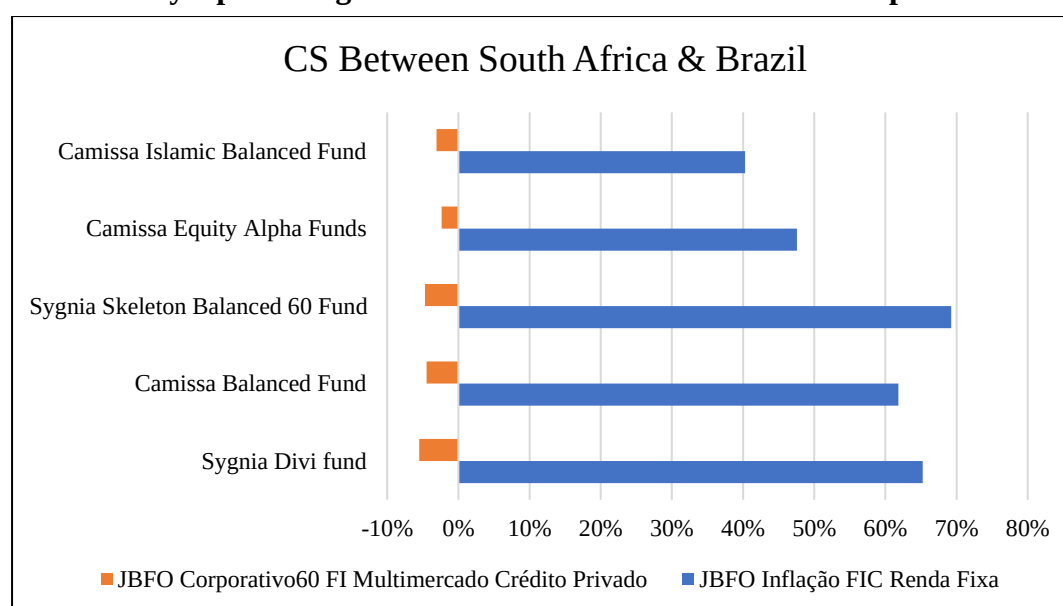


Figure 73 reports on the summary of the common style percentage between South African and Chinese portfolios for investors with a moderate tolerance. The highest common style percentage was between Sygnia Dividend fund and L&G E Fund UCTIS (85.60%).

Figure 73

Common style percentage between South African and Chinese portfolios for moderate risk

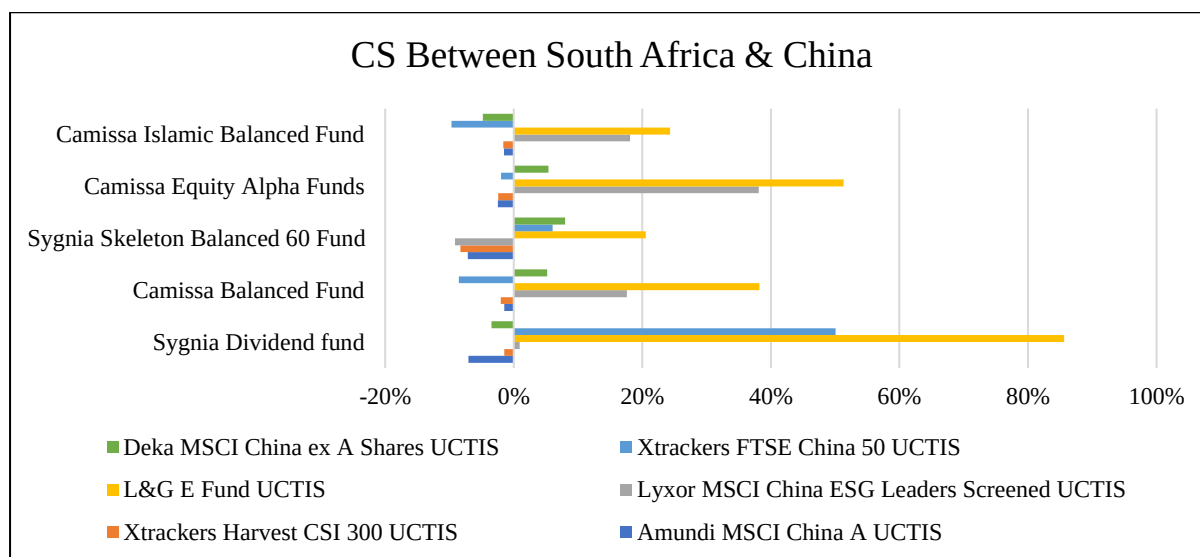


Figure 74 reports on the summary of the common style percentage between South African and Brazilian portfolios for investors with a low tolerance. The highest common style percentage was between Ninety-One Diversified Income Fund and *CFO Liquidez Multimercado Crédito Privado* (92.13%).

Figure 74

Common style percentage between South African and Brazilian portfolios for low risk

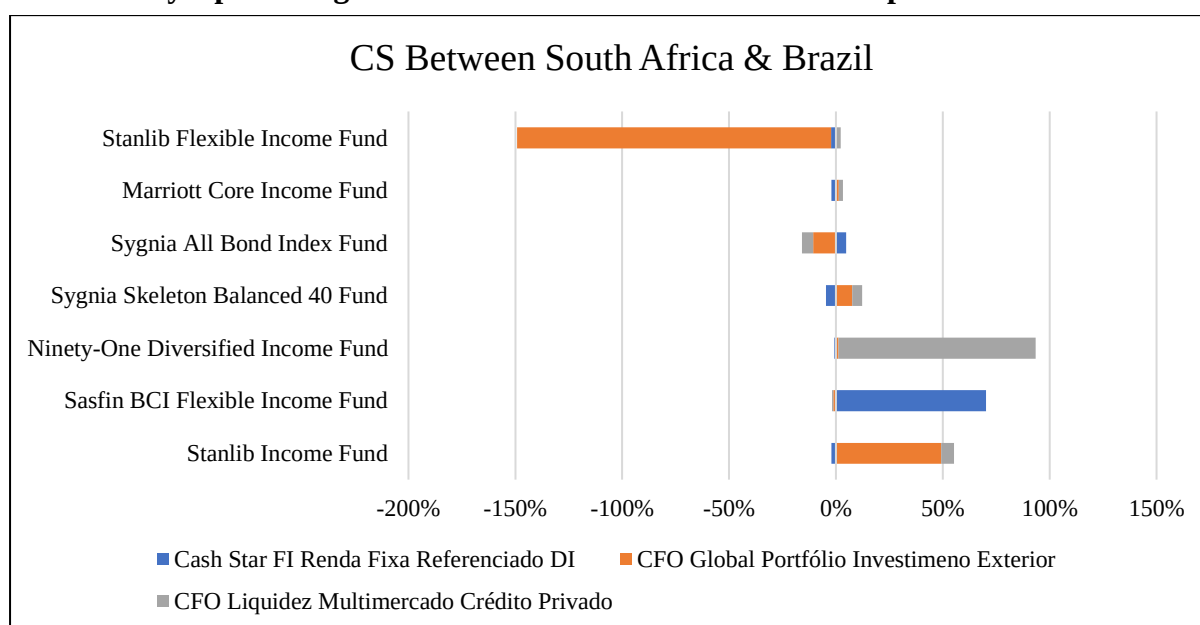


Figure 75 reports on the summary of the common style percentage between South African and Chinese portfolios for investors with a low risk tolerance. The highest common style percentage was between Sygnia Skeleton Balanced 40 Fund and Xtrackers II Harvest China Government Bond UCITS (2.54%%).

Figure 75

Common style percentage between South African and Chinese portfolios for low risk

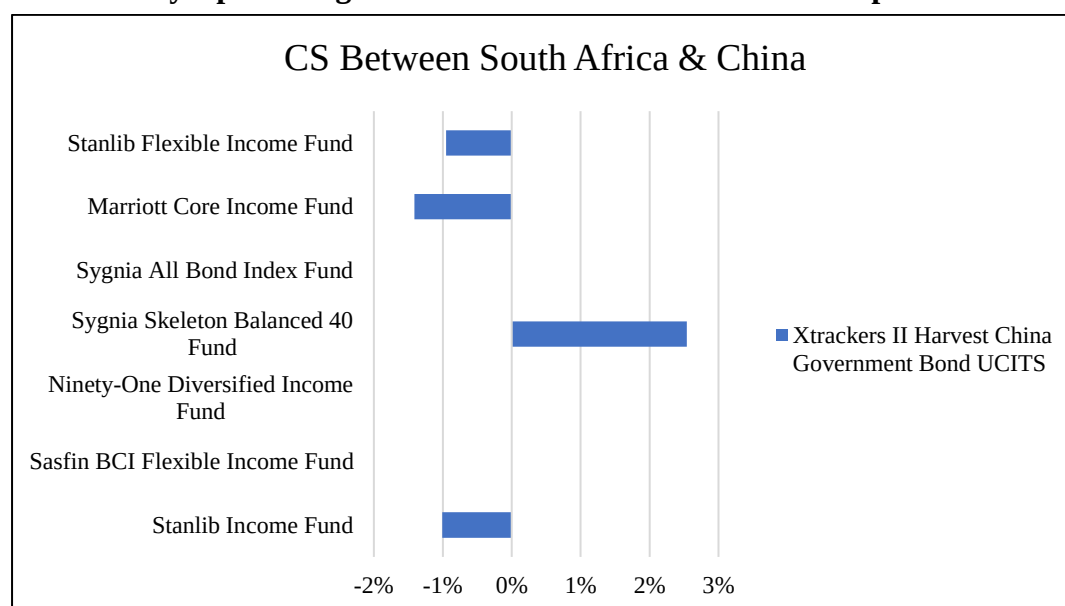


Figure 76 reports on the summary of the common style percentage between Indian and Brazilian portfolios for investors with a high-risk tolerance. The highest common style percentage was between Mirae Asset Large Cap Fund and *Composite Ações FI Ações* (100.51%).

Figure 76

Common style percentage between Indian and Brazilian portfolios for high risk

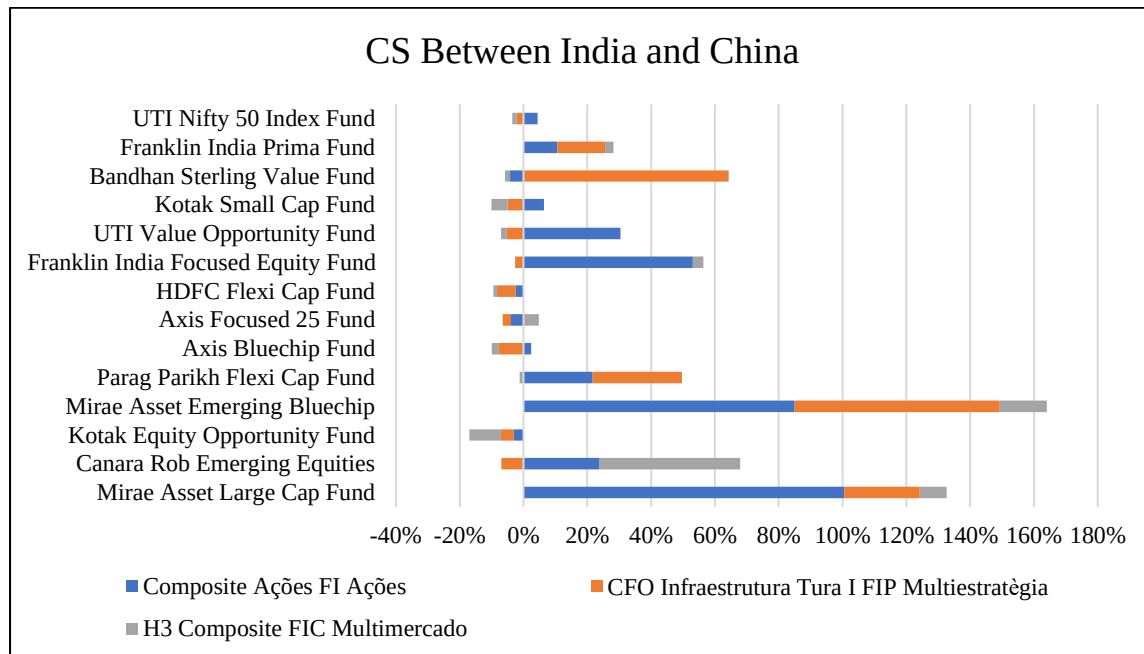


Figure 77 reports on the summary of the common style percentage between Chinese and Brazilian portfolios for investors with a high risk tolerance. The highest common style percentage was between iShares Dow Jones China Offshore UCTIS and *CFO Infraestrutura Tura I FIP Multiestratégia* (60.79%).

Figure 77

Common style percentage between Chinese and Brazilian portfolios for high risk

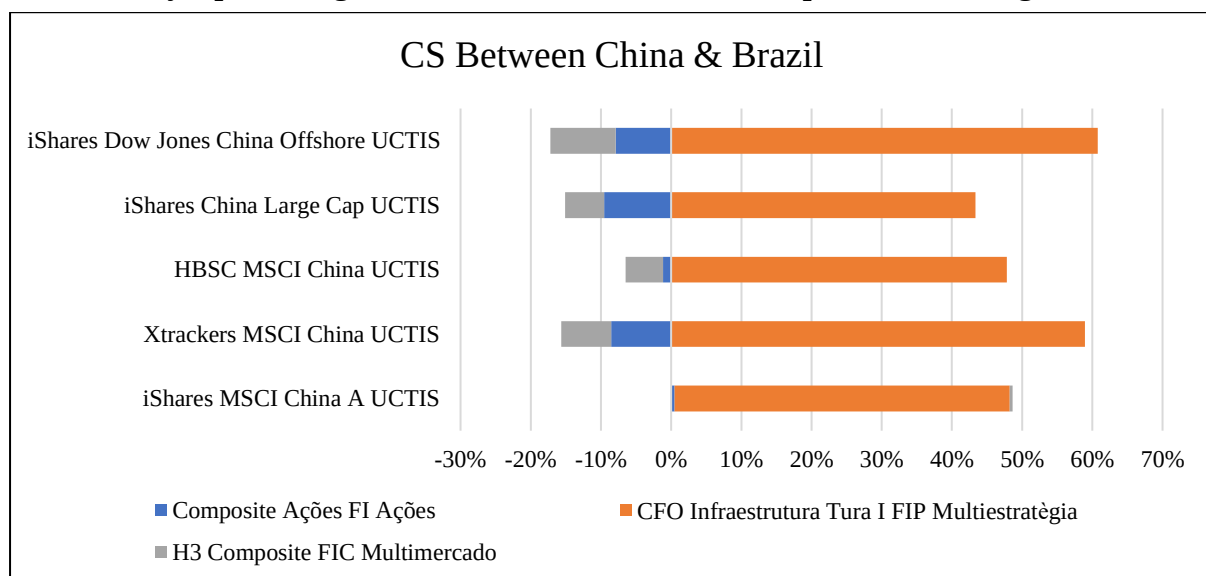


Figure 78 reports on the summary of the common style percentage between Chinese and Brazilian portfolios for investors with a moderate tolerance. The highest common style percentage was between L&G E Fund UCTIS and *JBFO Inflação FIC Renda Fixa* (90.62%).

Figure 78

Common style percentage between Chinese and Brazilian portfolios for moderate risk

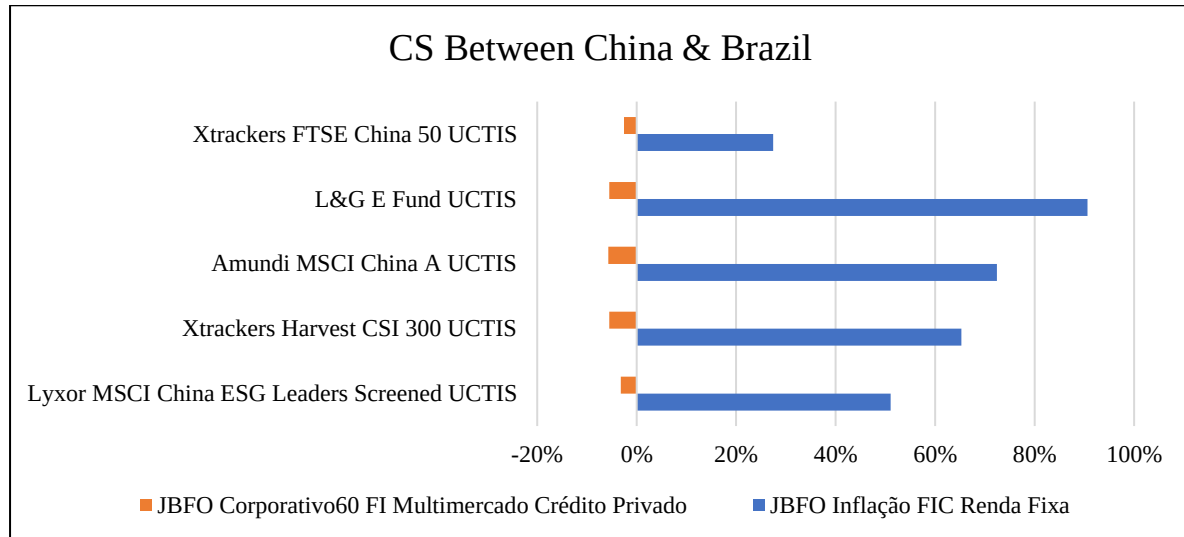


Figure 79 reports on the summary of the common style percentage between South African and Brazilian portfolios for investors with a high-risk tolerance. The highest common style percentage was between Xtrackers II Harvest China Government Bond UCITS and *CFO Liquidez Multimercado Crédito Privado* (61.87%)

Figure 79

Common style percentage between Chinese and Brazilian portfolios for low risk

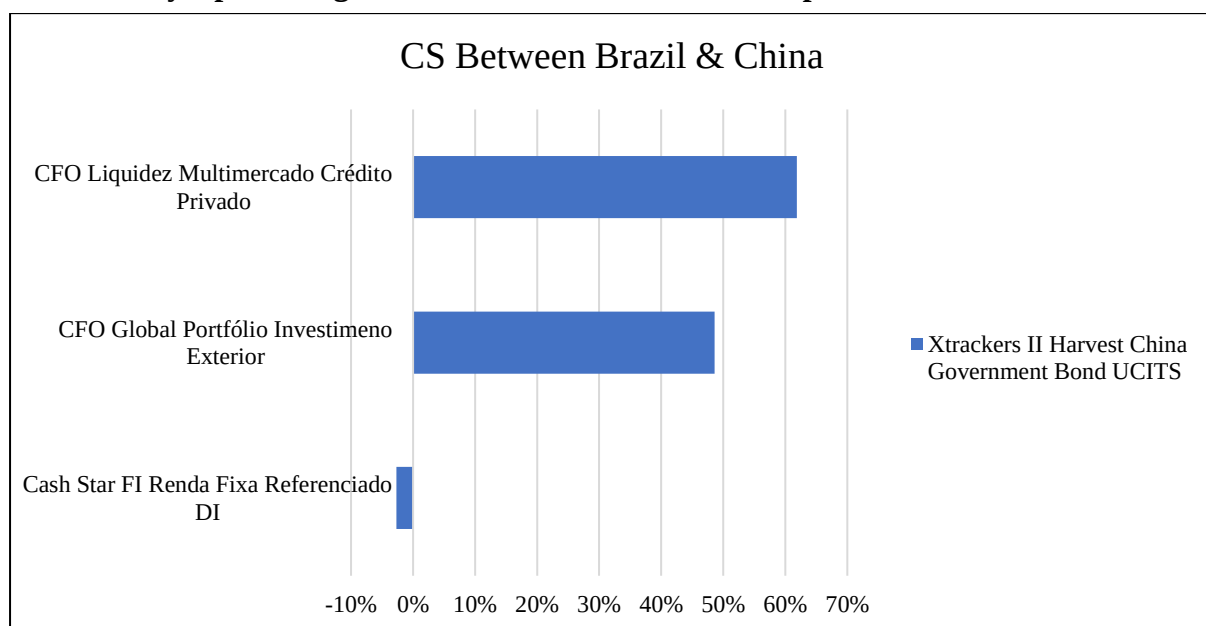
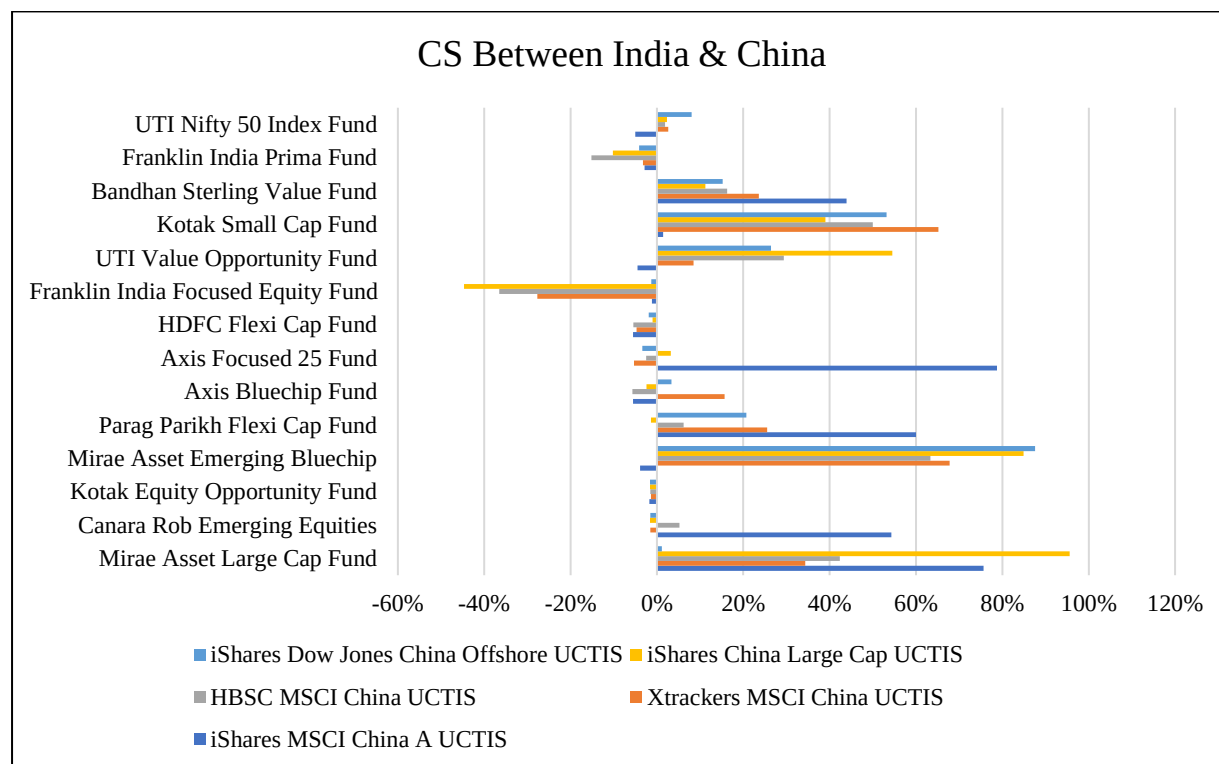


Figure 80 reports on the summary of the common style percentage between Chinese and Indian portfolios for investors with a high-risk tolerance. The highest common style percentage was between Mirae Asset Large Cap Fund and iShares China Large Cap UCTIS (95.56%).

Figure 80

Common style percentage between Chinese and Indian portfolios for high risk



5 Discussion

This section discusses the results of this research hypothesis: how the recommended portfolios from the robo-advisors perform before and after fees, and whether the recommended portfolios can deliver performance comparable to their relative benchmark. Additionally, it provides insight into why some robo-advisors perform better than others, explaining differences in performance before and after the fees. It is important to note that there was a limitation during the data collection process. Due to the Russia-Ukraine war of 2022. The data platform Bloomberg has posed sanctions on Russia. Therefore, leading to a removal of all Russian ETFs. The discussion section will therefore cover South Africa, India, China and Brazil and implications of the results.

5.5.1 Brazil

Figures 1-3 report on the summary of the Sharpe ratio for portfolios that cater for investors with a high, moderate, and low risk tolerance before and after fees. The portfolios reported a negative Sharpe ratio between 2015 and 2022 for the high, moderate, and low risk tolerance, which indicates an underperformance. A negative Sharpe ratio indicates that the total portfolio risk is not being compensated by the return. The *Composite Ações FI Ações* and *CFO Infraestrutura Tura I FIP Multiestratégia* slightly outperformed the benchmark in 2020. This indicates that both portfolios were able to recover towards the end of the year despite the hits in March 2020 due to the COVID-19 pandemic (Status Invest, n.d.). In 2021, the performance difference between all the portfolios and benchmark could have been because of the rise in interest rate and investor preferences changed from stocks to bonds resulting in a decline in stock prices and purchasing power tends to decrease when interest rates rise which leads to decreased revenue for business, thus resulting in a decline in stock prices (ECLAC, U. ,2021). Despite the variance in 2021 for all risk tolerances, the portfolios did perform similar to the benchmark. This is in line with the work of Puhle (2019). The *CFO Global Portfólio Investimeno Exterior FIC Multimercado* are a multi-market portfolio that has exposure to different foreign markets and the portfolio slightly outperformed the benchmark in 2020, this could be due the currency fluctuations in relation to the US currency as local investors would have benefited from a Brazilian currency depreciation. The reduction in the portfolio performance after fees were considered were insignificant.

Figures 4-6 report on the summary of the Treynor ratio for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. The portfolios reported a negative Treynor ratio for the years 2015, 2020 and 2022 for the high risk tolerance. The Treynor ratio was negative for all portfolios in 2018 and 2022 for moderate risk tolerance and positive Treynor ratios for the years 2015, 2016, 2020, and 2022 for low risk tolerance. In comparison with the Sharpe ratio, a negative Treynor ratio indicates that the portfolio has underperformed relative to its market risk. In 2015, Brazil's economy experienced a recession mainly due to low commodity prices and a sluggish economic growth and this could be reason for the portfolio underperformance in the same year (British Broadcasting Corporation, 2016). The impact of the COVID-19 pandemic could also reason for the portfolio performance underperformance in 2020.

Figures 7-9 report the summary of the Jensen's Alpha for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. All portfolios report a negative Jensen's Alpha. This could suggest that the portfolio underperforms compared to the benchmark. This is as expected as the robo-advisors are not expected to outperform the benchmark (Puhle, 2019). However, *CFO Global Portfólio Investimeno Exterior FIC Multimercado* slightly outperformed the benchmark in 2016.

Figures 10-12 report the summary of the manipulation-proof performance measure for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. All the portfolios report a positive manipulation-proof performance measure and investors with the same risk tolerance have funds that have similar manipulation-proof performance results. This is as expected as portfolios with the same risk profiles will have the similar results. Based on the results, there is no indication that there was manipulation of the performance measures.

5.5.2 India

Figure 13&14 reports the summary of the Sharpe ratio of investors with high risk tolerance before and after fees. All portfolios report a negative Sharpe ratio between 2015 and 2022, which indicates that the total portfolio risk is not being compensated by the return. The decline in commodity prices and oil prices, decrease in corporate earnings and the volatility in the equity market in 2015 could potentially be the reason for the decline in the portfolio performance. (Business Standard, 2015). The movements in global politics, changes to

domestic policies, increase in the crude oil prices in 2016 could be the reason for the decline in portfolio performance in 2016. (Anand, 2016). Furthermore, in 2017, the crude oil prices and rising interest rates remained an issue for India and could have led to a decrease in portfolio performance (Indo-Asian News Service, 2019). The covid-19 pandemic is the main reason for underperformance in 2020. Overall, the portfolios still performed close to the benchmark and performance reduced after fees were considered.

Figure 15&16 reports the summary of the Treynor ratio of investors with a high risk tolerance before and after fees. All portfolios report a negative Treynor ratio and still perform similar to the respective benchmarks before and after fees. Kotak Small Cap Fund has a positive Treynor ratio in year 2021 but is an immaterial ratio. The fund experienced strong risk-adjusted returns after some improvement in various sectors such as consumer staples and this might be the reason for the slight outperformance in 2021 (Meshram, 2024). The portfolios still performed close to the benchmark and performance reduced after fees were considered.

Figure 17&18 reports the summary of the Jensen's Alpha of investors with a high risk tolerance before and after fees. There were some portfolios that reported a positive alpha and others that reported a negative alpha before and after fees were considered. This suggests that there are portfolios in specific years that outperformed the respective benchmark and others that underperformed to the respective benchmark. This does not align with Puhle's (2019) conclusion that robo-advisors are not expected to outperform the market. FundsIndia did not provide any indication if there were portfolios that followed an active management style in the specific years that the portfolios outperformed the respective benchmark.

Figure 19&20 reports the summary of the manipulation proof performance measure for investors with a high risk tolerance before and after fees. All the portfolios report a positive manipulation-proof performance measure before and after fees and changes were relatively small. This indicates that investors with the same risk tolerance have funds that have similar manipulation-proof performance results. This is as expected as portfolios with the same risk profiles will have similar results.

5.5.3 China

Figures 21-25 report the summary of the Sharpe ratio for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. Before fees, all portfolios report a negative Sharpe ratio and perform similar to the benchmark with the exception of the HBSC MSCI China, iShares MSCI China A UCITS, Xtrackers Harvest CSI 300, Amundi MSCI China A UCITS, and L&G E Fund UCITS, which slightly outperformed the benchmarks in 2020. This is mainly due to the rise in the use of e-commerce, online shopping and tech services in the technology sector during the COVID-19 pandemic that could be the reason for the slight outperformance in 2020 (China-Britain Business Council, n.d). The portfolios still performed close to the benchmark and after fees, the portfolios still performed similar to the benchmark.

Figures 26-30 report the summary of the Treynor ratio for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. All portfolios report a negative Treynor ratio before and after fees. However, the iShares MSCI China A UCTIS, HBSC MSCI China UCTIS, Xtrackers Harvest CSI 300, Amundi MSCI China A UCTIS and L&G E Fund UCTIS in year 2020 has a positive Treynor Ratio though the ratio is significantly small. Furthermore, there were portfolios that still underperformed and did not perform similar to the benchmark such as the Deka MSCI China ex A Shares UCTIS, Amundi MSCI China A UCITS and L&G E Fund UCTIS in 2020. This suggests that the conclusion of Puhle (2019) does not always hold within certain portfolios that are recommended by the robo-advisor.

Figures 31-35 report the summary of the Jensen's alpha for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. There are some portfolios that slightly outperformed the benchmark and others that underperformed compared to the benchmark. This suggests that the conclusion of Puhle (2019) does not always hold within certain portfolios as the recommended portfolios are not expected to outperform the respective benchmarks. This might also suggest that some portfolios follow an active management style.

Figures 36-40 report the summary of the manipulation-proof performance measure for portfolios for investors with a high, moderate, and low risk tolerance before and after fees. Before and after fees, the portfolios report a positive manipulation-proof performance measure and investors with the same risk tolerance have funds that have similar manipulation-proof

performance results. This is as expected as portfolios with the same risk profiles will have the similar results.

5.5.4 South Africa

Figures 41-46 report on the summary of the Sharpe ratio for investors with high, moderate, and low risk tolerance before and after fees. There were no performance differences due to the small charge fee on each portfolio thus having little effect on the performance of the portfolios. The portfolios reported a positive and negative Sharpe ratios between 2015 and 2022 and performed similar to the respective benchmark. This is in line with the hypothesis by Puhle (2019) that this is expected of the portfolios recommended by the robo-advisors which is to follow a passive investment strategy and not to expect the portfolios to outperform the benchmark. However, the year 2021 had all portfolios slightly outperform the benchmarks and this is due to positive market sentiment around rising of commodity prices, easing of COVID-19 lockdown restrictions and the GDP growth in the first half of 2021 (National Treasury, 2021). Furthermore, the portfolios meant to mimic the STeFi composite benchmark had varying performance throughout the years.

There was a significant decrease from 2019 to 2020 in all the portfolios and this was due to the effects of the COVID-19 pandemic. The global outlook on South Africa in 2020 was pessimistic (Sygnia, 2020). The equity market in South Africa declined rapidly in 2020 and the property sector suffered the most decline due to months of lockdown, remote work, and little to no economic activity. In addition, the South African bonds market had an increase in the sale of bonds domestically. However, due to the credit rating downgrade, South African bonds may have been viewed as a risky investment by foreign investors which resulted in the disposal of the bonds (PricewaterhouseCoopers [PwC], 2020). Diversification would have been useful in this aspect.

Figures 47-52 report on the summary of the Treynor ratio of the portfolios for investors with high, moderate, and low tolerance before and after fees. There was slight performance differences before and after fees were considered. The portfolios had both positive and negative Treynor ratio throughout the years. This is as expected as the portfolios recommended by the robo-advisor are not expected to outperform the benchmark. The recommended portfolios still performed similar to the respective benchmarks.

Figures 53-58 report on the summary of the Jensen's Alpha for investors with high, moderate, and low risk tolerance before and after fees. There were no performance differences before and after fees were considered. All the portfolios had both positive and negative Jensen's Alpha. The outperformance of the portfolios is attributed to the fact that some external funds have external managers who may follow an active management style. Puhle's (2019) conclusion that the robo-advisors do not outperform the benchmark does not seem to hold here. In 2016, the equity market benefited from adjustments in the monetary policy post the recession. This led to a search in yield, resulting in South Africa receiving inflows of bonds and equity from international investors (Donnelly, 2017). The company valuations were also a factor as to why the equity market performed well. The JSE has dual-listed companies that receive an earnings portion from the offshore company which has an impact on the index returns which is included in the portfolio. In 2016, the property market performed well. The financial market was extremely volatile which resulted in the investment in property as an asset class as a preference and the demand for housing increased from first time buyers (Sygnia, 2016).

Figures 59-64 report the summary of the MPPM for portfolios that cater to investors with high, moderate, and low risk tolerance before and after fees. All the portfolios report a positive manipulation-proof performance measure and investors with the same risk tolerance have funds that have similar manipulation-proof performance results. This is as expected as portfolios with the same risk profiles will have similar results.

5.6 Asset allocation

5.6.1 Brazil

Figure 65 is a summary of the estimated asset allocation for Brazil. There are some discrepancies between the estimated asset allocation and the actual asset allocation reported for the portfolios. For instance, the *Cash Star FI Renda Fixa Referenciado DI* has most of its assets in bonds (95%) and the rest in real estate but the estimated asset allocation reports that there is some exposure to emerging and developed market equity. *CFO Global Portfólio Investimento Exterior* provides no indication about corporate and government bonds yet the estimated asset allocation reports that there is exposure in those bonds similarly with the *CFO Liquidez Multimercado Crédito Privado*. The rest of the portfolios for Brazil share the same sentiment that the estimated asset allocation and the reported asset allocation display some differences,

yet it is important to note that this measure is meant to provide additional insights as to why some recommended portfolios by robo advisors perform differently than others. The source of asset classes or asset class allocation may be a reason to performance differences.

5.6.2 India

Figure 66 is a summary of the estimated asset allocation for India. There are some discrepancies between the estimated asset allocation and the actual asset allocation reported for the portfolios. Almost all the portfolios listed only have exposure to developed and emerging market equities and yet the estimated asset allocation reports that these portfolios have real estate and corporate and government bonds as part of the asset allocation. Mirae Asset Large Cap Fund, Kotak Equity and Franklin India Focused Equity Fund report a large asset allocation portion to developed and emerging market equities which mirrors the actual asset allocation of the portfolios. However, these portfolios still report that there is estimated asset allocation in real estate and corporate and government bonds.

5.6.3 China

Figure 67 is a summary of the estimated asset allocation for China. There are also some discrepancies between the estimated asset allocation and the actual asset allocation reported for the portfolios. For instance, the iShares MSCI China A reports a large portion of the portfolio is allocated to equities and yet the estimated asset allocation reports more exposure to corporate and government bonds similar to the L&G E Fund mostly has emerging market and developed market equity and the estimated asset allocation reports the corporate bond being the largest asset allocation portion. The rest of the portfolios for China share the same sentiment that the estimated asset allocation and the reported asset allocation display some differences.

5.6.4 South Africa

Figure 68 is a summary of the estimated asset allocation for South. There are also some discrepancies between the estimated asset allocation and the actual asset allocation reported for the portfolios. For instance, the Sygnia Dividend Fund has only 100% equity allocation and the estimated reported asset allocation indicates that the real estate, corporate and government bond combined make up most of the portfolio. Similarly, the Sygnia SWIX Index fund and Sygnia Top 40 Index Fund reports the same discrepancy. The Sygnia All Bond Index has a 100% real estate allocation, and the estimated asset allocation reported indicates that the emerging market

equity makes up the majority of the portfolio. Additionally, Sygnia Equity Fund has a 100% equity allocation and the estimated asset allocation reports that much of the portfolio is allocated to developed and emerging market equity therefore, not much discrepancy exists there. The rest of the portfolios still display the same sentiment that the estimated asset allocation and the reported asset allocation display some differences.

5.6.5 Common style analysis

Figure 69 reports the common style percentages between South African and Brazilian portfolios for investors with high risk. A zero and negative common style percentage between portfolios indicates that the portfolios have different investment styles i.e., the portfolios do not have the same exposure to the same asset classes. *CFO Infraestrutura Tura I FIP* and Sygnia Listed Property Index Fund had the highest common style percentage. This is as expected as both portfolios have the same asset class (real estate) hence the high common style percentage. Similarly, *CFO Infraestrutura Tura I FIP* holds a positive common percentage with Sygnia Top 40 Index Fund, Sygnia Skeleton Balanced 70 fund, Sygnia equity fund, Marriott Dividend Growth Fund, 36ONE BCI Equity fund, Coronation Top 20 fund, Foord Equity fund, PSG Equity fund, Old Mutual Global Equity and Allan Gray Orbis. This was as expected as all these portfolios include developed and emerging market equities. Additionally, Sygnia Listed Property Index Fund and *H3 Composite FIC Multimercado* have a percentage of 67.98% between them. This is also as expected as *H3 Composite FIC Multimercado* includes real estate as part of the portfolio although most of the portfolio holds emerging and developed market equity while Sygnia Listed Property Index Fund holds only 100% of property. Similarly, *H3 Composite FIC Multimercado* and Allan Gray Orbis Global have a small percentage of 4.28% between them and Allan Gray Orbis Global holds a 25% of real estate in its portfolio. The difference in investment styles between South African and Brazilian portfolios may be an explanation for performance differences.

Figure 70 reports the common style percentages between South African and Indian portfolios for investors with high risk. The highest was between Parag Parikh Flexi Cap Fund and Allan Gray Orbis Global Equity Feeder Fund (99.10%). This indicates that there is a similar investment style that exists between the portfolios, and Allan Gray Orbis Global Equity Feeder Fund holds 75% of equity in its portfolio while Parag Parikh Flexi Cap Fund holds 49.26% in

equity. The rest of the portfolios have a negative common style percentage, which can suggest that the portfolios have a different investment style due to different asset exposure. This can also be one of the many reasons that explains performance differences between the portfolios.

Figure 71 reports the common style percentages between South African and Chinese portfolios for investors with high risk. Sygnia Listed Property Index Fund and Xtrackers MSCI China UCTIS (88.78%) had the highest common style percentage. Xtrackers MSCI China holds a relatively small percentage in real estate while the Sygnia Listed Property holds 100% of real estate in its portfolio. This can suggest that the portfolios may have similar investment styles. The rest of the portfolios have a negative common style percentage.

Figure 72 reports the common style percentages between South African and Brazilian portfolios for investors with moderate risk. The highest was between Sygnia Skeleton Balanced 60 Fund and *JBFO Inflação FIC Renda Fixa* (69.26%%). This can suggest that the portfolios may have similar investment styles, which means the portfolios have exposure to the same asset class. The rest of the portfolios have a negative common style percentage.

Figure 73 reports the common style percentages between South African and Chinese portfolios for investors with moderate risk. Sygnia Dividend fund and L&G E Fund UCTIS (85.60%%) had the highest common style percentage. This can suggest that the portfolios may have similar investment styles, which means the portfolios have exposure to the same asset class. The rest of the portfolios have a negative common style percentage. This can indicate that different investment styles between the portfolios in South African and Chinese.

Figure 74 reports the common style percentages between South African and Brazilian portfolios for investors with low risk. The highest was between Ninety-One Diversified Income Fund and *CFO Liquidez Multimercado Crédito Privado* (92.13%). Both portfolios have exposure to similar assets. This can suggest that the portfolios may have similar investment styles even though the portfolios may not have exposure to the same asset class. The rest of the portfolios have a negative common style percentage.

Figure 75 reports the common style percentages between South African and Chinese portfolios for investors with low risk. Sygnia Skeleton Balanced 40 Fund and Xtrackers II Harvest China Government Bond UCITS (2.54%%) had the highest common style percentage. This can

suggest that the portfolios may have similar investment styles even though the portfolios may not have exposure to the same asset class. The rest of the portfolios have a negative common style percentage. This can indicate that different investment styles between the portfolios in South African and Chinese.

Figure 76 reports the common style percentages between Indian and Brazilian portfolios for investors with high risk. The highest was between Mirae Asset Large Cap Fund and *Composite Ações FI Ações* (100.51%). This suggests that both portfolios have exposure to the same asset class, in this case it is emerging and developed market equities. Most of the portfolios have a negative common style percentage. This can indicate that different investment styles between the portfolios in India and China.

Figure 77 reports the common style percentages between Chinese and Brazilian portfolios for investors with high risk. The iShares Dow Jones China Offshore UCTIS and *CFO Infraestrutura Tura I FIP Multiestratégia* (60.79%) had the highest common style percentage. This is primarily due to both portfolios being global portfolios that have exposure to multiple asset classes. Regarding these portfolios, the largest asset class exposure is the developed market equities. This suggests that the portfolios have the similar investment styles as these portfolios have exposure to the same asset classes. The portfolios with negative common style percentage indicates different investment styles between the portfolios as these portfolios might have different asset class exposure.

Figure 78 reports the common style percentages between Chinese and Brazilian portfolios for investors with high risk. The highest common style percentage was between *JBFO Inflação FIC Renda Fixa* and L&G E Fund (90.62%). This is as expected as both portfolios have exposure to the same asset class, which is emerging market equity. Similarly with the rest of the Chinese portfolios that have a high common style percentage with the *JBFO Inflação FIC Renda Fixa* portfolio. This suggests that the portfolios have the similar investment styles as these portfolios have exposure to the same asset classes.

Figure 79 reports the common style percentages between Chinese and Brazilian portfolios for investors with low risk. Xtrackers II Harvest China Government Bond and *CFO Liquidez Multimercado Crédito Privado* had the highest common style percentage (61.87%). This is as expected because the *CFO Liquidez Multimercado Crédito Privado* is a fixed income that

includes bonds as a majority portion of the portfolio similar with the Xtrackers II Harvest China Government bond. This suggests that these portfolios have a similar investment style as the portfolios have the exposure of the same asset class.

Figure 80 reports the common style percentages between Chinese and Indian portfolios for investors with high risk. The highest common style percentage was between Mirae Asset Large Cap Fund and iShares China Large Cap (95.56%). This is as expected as both portfolios have equities as the majority asset allocation. Similarly, high common style percentage between Canara Rob Emerging Equities and iShares China Large Cap and between Mirae Asset Emerging Bluechip and iShares China Large Cap is also mainly due to these portfolios having equities as a large portion in the portfolios. This suggests that these portfolios have similar investment styles that exists between them. The portfolios with negative common style percentages such as UTI Value Opportunity Fund and iShares MSCI China A to name a few merely suggests that these portfolios do not have the same asset class exposure and could be an explanation as to why performance differences exist between these portfolios.

6 Conclusion

In this research, the performance of robo-advisors in BRICS countries apart from Russia is measured and the recommended portfolios perform similar to the benchmark as the portfolios are not expected to outperform the benchmark. In addition, the asset allocation section is used to explain performance differences between the portfolios and why some portfolios perform better than the others. It is found that the performance of robo-advisors is dependent on the robo-advisor an investor chooses to invest in and the country, as some countries have portfolios that slightly outperform the respective benchmark. In Brazil, there were portfolios that did not perform similar to the benchmark before and after fees were considered and outperformed the benchmark. This was expected as there was a disclaimer that the robo-advisor has portfolios that are actively managed and some that are passively managed. In India, the recommended portfolios performed similar to the benchmark before and after fees and do not outperform the benchmark which suggests a passive management style. In China, most portfolios performed similar to the benchmark before and after fees. However, since the robo-advisor uses an external broker to provide the user access to ETFs, there were some portfolios that outperformed the benchmark, which suggests that some portfolios could be actively managed. Lastly in South Africa, it was found that the portfolios performed similar to the benchmarks and that the performance of the external portfolios with external managers suggests an active management style as these portfolios outperform the benchmark and there was a slight performance difference before and after fees in all the countries. Furthermore, it was found that there were some portfolios that shared the similar investment styles i.e., having exposure to the same asset and other portfolios that had different investment styles, and this can be one of the explanations for performance differences between the portfolios in BRICS. It was also found that the estimated asset allocation for each country had some discrepancies. However, the estimated asset allocation is used to determine if the asset allocation in each portfolio is also one of the reasons for performance differences between the portfolios. It is important to also note that robo advisor fees, rebalancing of portfolios and a different asset class group that was not tested here and could also be the reason for performance differences.

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APPENDICES

Appendix A

Table A.1

Benchmarks in South Africa

Benchmark
JSE Shareholder Weighted Index (SWIX)
JSE Top 40 Index
JSE All Bond Composite Index
JSE SA Listed Property Index
JSE All Share
JSE Capped Shareholder Weighted Index
Satrix MSCI World Index
Median of South African Multi-Asset-Low Equity Category
Median of South African Multi-Asset-Medium Equity Category
Median of South African Multi-Asset-High equity Category
STeFi Composite
South African Multi-Asset-High Equity Funds Mean
South African Equity General Funds Mean

Table A.2

Benchmarks in India

Benchmark
NIFTY 100 – TRI
NIFTY Large Midcap 250 – TRI
NIFTY 500 – TRI
S&P BSE 100 - TRI

Benchmark
S&P BSE 500 - TRI
NIFTY 50 – TRI
Nifty Small Cap 250 - TRI
Nifty Midcap 150 - TRI

Table A.3
Benchmarks in China

Benchmark
MSCI China A Inclusion Index
CSI 300 Total Returns Index
MSCI China Total Returns Index
100% MSCI China Net
FTSE China 50 Index
MSCI China Select ESG Rating
MSCI China A Index
MSCI China ex A Shares Index
Dow Jones China Offshore 50 Index

Table A.4
Benchmarks in Brazil

Benchmark
Certificado de Depósito Interbancário

Appendix B

Table B.1

Each country and its risk-free rate

Country	Risk-free Rate
Brazil	<i>Certifiicado de Depósito Interbancário (CDI)</i>
Russia	Russia Interbank Rate (MIACR)
India	Mumbai Interbank Offer Rate (MIBOR)
China	China Interbank Offer Rate (CHIBOR)
South Africa	Johannesburg Interbank Average Rate (JIBOR)

Appendix C

Table C.1
Characteristics of BRICS

Country	Selected Robo Advisor	Number of portfolios	Assumed Investment Strategy	Management/Robo-advisor Fees
Brazil	Magnetis	Eight	Passive	0.5% management fees annually.
India	FundsIndia	Fifteen	Passive	Each portfolio has its own management fees
China	Scalable Capita	Twelve	Passive	Each portfolio has its own management fees
South Africa	Sygnia	Twenty-four	Passive	Each portfolio has its own management fees