Mutual Fund Performance, Performance Persistence and Impact of Unprecedented Factors on Mutual Fund Performance in Saudi Arabia

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Abstract

This empirical study comprehensively analyses the performance of active and passive equity mutual funds in Saudi Arabia during 2010–2020. This analysis also encompasses subsample periods coinciding with various significant market events (SMEs), such as the periods before and after the financial reforms of 2015, the Saudi Arabian market-specific financial crises in 2014–2016 and 2019–2020, and bullish and bearish market conditions. Furthermore, it explores whether mutual fund risk-adjusted performance varies when using different benchmark indices. In addition, this study examines whether the performance persistence of individual active funds is linked to genuine stock-picking skills or is merely a result of pure luck. Moreover, given the extreme participation of individual traders in the Saudi Arabian market, the study examines whether investor sentiment influences mutual fund performance, along with other factors, such as oil price volatility, compliance with Islamic law, management expense ratios, fund flows, fund age and fund size. Last, it measures the impact of the spread of the coronavirus disease (COVID-19), including the increase in confirmed new cases and confirmed fatalities, on mutual fund performance during the peak of the pandemic in Saudi Arabia.

The study applied various econometric models to examine the proposed hypotheses. First, the mean-difference measure was used to calculate the benchmark-adjusted performance, while time-series regression-based models (specifically, the Jensen single-factor model and the Fama–French–Carhart 6-factor model) were applied to estimate the risk-adjusted performance. Further, structural break tests were used to examine significant variations in fund performance across SMEs and to compare the performance of both active and passive mutual funds. Second, a bootstrap statistical technique was employed to investigate whether the performance persistence of individual active funds can be significantly attributed to genuine stock-picking skills or was merely

the result of luck. Last, a panel regression model was used to examine both the potential impact of investor sentiment and the impact of COVID-19 spread on mutual fund performance.

The findings regarding the benchmark-adjusted and risk-adjusted performance indicate that active funds outperformed the benchmark indices. However, there is no evidence to support the outperformance of passive funds to these indices. Moreover, structural break tests demonstrated a significant superior performance of active funds over passive funds. In addition, the empirical evidence revealed that the performance of mutual funds during periods of SMEs differed significantly from that in the overall sample period. Regarding the investigation of performance persistence, the study's findings confirm that genuine stock-picking skills underlie the observed performance persistence across a large number of active funds. Turning to the investigation of the potential influence of investor sentiment on fund performance, the findings suggest a positive and significant impact of investor sentiment on active mutual fund performance. In contrast, the impact of investor sentiment on passive fund performance is comparatively subdued. Last, the study finds that the proliferation of the COVID-19 pandemic exerted a significant and negative impact on the performance of active mutual funds.

Keywords: stock market, active funds, passive funds, fund performance, performance persistence, significant market events, alpha, investor sentiment, COVID-19, Saudi Arabia

Declaration

I, Haidar Alqadhib, declare that the PhD thesis entitled 'Mutual fund performance, performance persistence, and impact of unprecedented factors on mutual fund performance in Saudi Arabia' is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures.

Signature Date: 15/ 12/ 2023

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List of Abbreviations

AUM	Assets under management
BFS	Behavioural finance school
CAPM	Capital asset pricing model
CDF	Cumulative density function
CMA	Conservative minus aggressive
CWF	Change in weekly fatalities
CWI	Change in weekly new infections
EMH	Efficient market hypothesis
ETFs	Exchange-traded funds
FF3FM	Fama–French three-factor model
FF5FM	Fama–French five-factor model
FFC4FM	Fama–French–Carhart four-factor model
FFC6FM	Fama–French–Carhart six-factor model
FTSE	Financial Times Stock Exchange
GCC	Gulf Cooperation Council
GDP	Gross domestic product
GRS	Gibbons, Ross and Shanken (1989)
HML	High minus low
IPCSI-SA	Ipsos Primary Consumer Sentiment Index – Saudi Arabia
IPO	Initial public offering
MAA	Mean absolute alpha
MOM	Momentum
MPT	Modern portfolio theory

MSCI	Morgan Stanley Capital International
MSCI-SADI	Morgan Stanley Capital International Saudi Arabia Domestic Index
NAV	Net asset value
OLS	Ordinary least squares
QFIIs	Qualified Foreign Institutional Investors
REIT	Real estate investment trust
RMW	Robust minus weak
S&P	Standard & Poor’s
S&P GSCI	Standard & Poor’s – Goldman Sachs Commodity Index
S&P-SADITR	Standard & Poor’s Saudi Arabia Domestic Index Total Return
SACMA	Saudi Arabian Capital Market Authority
SAMA	Saudi Central Bank
SAR	Saudi Arabian Riyal
SFM	Single-factor model
SMB	Small minus big
SMEs	Significant market events
Tadawul	The Saudi Stock Exchange
TASI	Tadawul All Share Index
TFS	Traditional finance school
TNA	Total net assets
US	United States
USD	United States Dollar
VIF	Variance inflation factor

Chapter 1: Introduction

1.1 Research Background

Equity mutual funds serve as financial intermediaries that provide diversification opportunities to individual investors by pooling their relatively small capital contributions and investing the collected capital in a wide range of securities. Mutual fund managers are responsible for creating and managing well-diversified investment portfolios using the funds collected. They handle administration and record keeping and provide diversification benefits to investors at lower transaction costs (Bodie et al., 2010, p. 84). Mutual funds can be classified according to two main investment strategies: active and passive. Managers of active funds conduct fundamental economic research and technical analyses to select underpriced securities or to time major fluctuations in the market in an attempt to achieve higher returns than the market. In contrast, passive funds, including index funds and exchange-traded funds (ETFs), aim to track the returns and risks of their respective benchmark indices (Haslem, 2009). Appendix A details the differences between active and passive funds.

Notably, mutual funds play a pivotal role in capital markets, facilitating capital accumulation. Over the past decade, worldwide, the mutual fund industry has experienced significant growth, with assets under management (AUM) increasing by 120%, from USD32.3 trillion to 71.1 trillion (Investment Company Institute, 2022). In particular, according to the Saudi Arabian Capital Market Authority (SACMA), mutual funds in the country were managing approximately USD56 billion by 2020, making it the largest mutual fund industry in the Middle East and North Africa region (Capital Market Authority, 2020). The size of this industry reflects its importance in the local capital market.

The presence of mutual funds is important for ensuring national economic development and attracting international investors. First, a significant proportion of international capital inflows occur through mutual funds, which has a positive effect on the country's balance of payments. Furthermore, foreign investment in mutual funds can serve as an indicator of confidence in the host country's economy and financial markets. This influx of foreign investment also stimulates demand for the country's currency, resulting in currency appreciation. Second, mutual funds play a vital role in granting international investors indirect access to the Saudi equity market. The integration of the Saudi equity market with leading emerging market indices in 2015 resulted in its weightage amounting to 2.6% in the Morgan Stanley Capital International (MSCI) index, 3% in the Financial Times Stock Exchange (FTSE) Russell index and 2.57% in the Standard and Poor's (S&P) index.[1] Consequently, international mutual funds and foreign investors, particularly those focusing on emerging markets, who lack the necessary qualifications to invest in the Saudi equity market directly, are compelled to include Saudi Arabian mutual funds in their portfolios to align with the performance of these indices. Therefore, mutual fund performance is of great importance to the SACMA and investors.

However, in the finance field, the performance of mutual funds has attracted critical questioning. Modern portfolio theory (MPT), in line with the efficient market hypothesis (EMH), states that investors achieve the maximum expected return for a given level of risk, implying that no investor can outperform the overall market consistently (Lintner, 1965b; Markowitz, 1952; Sharpe, 1964; Treynor, 1962). Studies supporting the EMH have provided empirical evidence that managers add no value to an investor's portfolio (Carhart, 1997; Ferreira et al., 2013; Jensen, 1968; Malkiel, 1995). Conversely, behavioural finance theory argues that noise in markets causes

[1] These weights were in the initial integration and were adjusted subsequently by comparing the weight of the Saudi equity market to that of all emerging markets.

markets to be somewhat inefficient (Black, 1986). This aspect may allow informed investors to outperform the market. This theory also has seminal empirical studies supporting its argument that managers may add value to an investor's portfolio (Daniel et al., 1997; Grinblatt & Titman, 1989, 1992, 1993; Ippolito, 1989; Kosowski et al., 2006, 2007; Wermers, 2000). To date, mutual fund performance is a topic of an ongoing debate, possibly due to differences in methodological approaches, such as the samples selected, survivorship bias in the sample, and issues related to the selection of the appropriate benchmark index and performance measuring models.

Significantly, the seminal academic works on mutual fund performance discussed thus far have predominantly focused on funds in the United States (US), primarily owing to the massive size of these funds. By 2020, approximately 10,000 US mutual funds were managing USD30 trillion out of the USD63 trillion invested worldwide—that is, about 48% of the global total net assets (Investment Company Institute, 2022).[2] The fierce competition among this large number of informed managers in a mostly efficient market such as the US market could minimise mutual fund performance, creating challenges in identifying outperforming funds (Jones & Wermers, 2011).

However, the mutual fund industry in Saudi Arabia presents a stark contrast. The number of equity mutual funds in the country is significantly smaller,[3] and these operate in a market with distinct characteristics. The Saudi equity market is often characterised as a weak-form stock market (Al-Ajmi & Kim, 2012; Budd, 2012; Butler & Malaikah, 1992; Syed & Bajwa, 2018), which is heavily influenced by oil market prices (Almohaimeed & Harrathi, 2013; Arouri et al., 2011; Arouri & Rault, 2010, 2012; Hammoudeh & Aleisa, 2004; Zarour, 2006), Moreover, the

[2] The cited organisation provides more details about the total net assets of US mutual funds since 2012, as against the global total net assets.

[3] The specific numbers and details regarding mutual funds in Saudi Arabia will be presented in Chapter 2.

market exhibits significant government ownership in market capitalisation, and individual traders dominate market trading activities (Tadawul, 2020). Thus, understanding the behaviour of mutual fund performance in this distinctive market is essential for developing a comprehensive picture of funds' performance and challenges.

However, the literature on mutual fund performance in Saudi Arabia is limited and lacks comprehensiveness. Only a few studies have explored the performance of Saudi mutual funds (Al Rahahleh & Bhatti, 2022; Ashraf, 2013; BinMahfouz & Hassan, 2012; Merdad et al., 2016). However, these studies have notable gaps, including methodological issues, the absence of a direct comparison between active and passive fund performance and the lack of comparison of mutual fund performance during long sample periods to that during significant market events (SMEs).

Hence, this thesis addresses three methodological issues to enhance the rigor of prior studies. First, it challenges the conventional use of the Tadawul All Share Index (TASI) as a sole benchmark for fund performance. To calculate TASI, the price levels of its constituents is used, which might not accurately measure some funds' performance, particularly that of funds with compounding returns from dividends. Recognising the pivotal role of the benchmark in measuring mutual fund performance (Fama & French, 2004; Grinblatt & Titman, 1989, 1994; Roll, 1977, 1978), this study uses and compares fund performance against three indices—TASI, Morgan Stanley Capital International Saudi Arabia Domestic Index (MSCI-SADI) and Standard & Poor's Saudi Arabia Domestic Index Total Return (S&P-SADITR).[4] The second methodological issue addressed is the use of an advanced asset pricing model. Earlier studies on the Saudi market used single-factor, three-factor or four-factor models, potentially resulting in inaccurate performance assessments because they neglected mutual fund investment styles. In contrast, this research adopts

[4] Details about these indices and their methodologies of computation are provided in Chapter 4.

the Fama–French–Carhart six-factor model (FFC6FM) (Carhart, 1997; Fama & French, 2015), a new approach in the context of Saudi Arabian mutual funds. Third, this thesis addresses an often-overlooked factor—survivorship bias—which critically influences conclusions about mutual fund performance (Malkiel, 1995).[5] In contrast to past studies on Saudi Arabia, the current research includes both existing and liquidated funds to control for survivorship bias, which contributes to the robustness of its results.

In the Saudi Arabian context, there is a notable gap in comprehensive examinations that directly contrast the performance of active funds against that of passive funds. While the finance field predominantly explores viable investment strategies, with a notable focus on active versus passive funds, studies in the Saudi context primarily focus on fund characteristics (Islamic funds v. conventional funds), resulting in a significant knowledge gap. It is crucial to note that indices, often employed in prior studies for adjusting fund performance, are non-investable and do not incur associated costs (Frino & Gallagher, 2001). Consequently, this issue renders the findings of studies reporting non-significant performance questionable, given the lack of real-world investment opportunities. Therefore, addressing this gap would offer an alternate, dependable perspective on the most prudent investment strategy to be adopted.

A primary objective of this study is to compare the performance of mutual funds measured over an extended period, specifically from January 2010 to December 2020, to their performance during subsample periods coinciding with SMEs. Studies on mutual fund performance in Saudi Arabia have frequently considered relatively short periods and have overlooked fund behaviour during SMEs. The study of fund performance within SMEs, encompassing financial crises pre and post the 2015 financial reforms, and phases of bullish and bearish market conditions, would

[5] Malkiel (1995) found that using data on only surviving (existing) funds results in a biased conclusion because their returns are 150 basis points higher than that of liquidated funds.

highlight the potential distinctive behaviour of mutual fund performance during these specific periods.

One crucial aspect under consideration is the distinct patterns that mutual fund performance may exhibit during financial crises compared with the patterns in normal market conditions. For instance, Moskowitz (2000) argued that investors' marginal utility of wealth increases during market downturns, leading to different investment behaviours. Empirical support for this argument is found in studies such as that of Kosowski (2011), which demonstrated that US mutual funds tend to deliver enhanced performance for investors during market downturns. However, in the Saudi Arabian context, two market-specific financial crises occurred between 2010 and 2020. The first crisis unfolded during 2014–2016, triggered by substantial declines in oil prices, while the second crisis transpired in 2019–2020, driven by severe oil price declines compounded by the global repercussions of the coronavirus disease (COVID-19) pandemic.

In addition, the major financial reforms of 2015 constitute a remarkable SME. In June 2015, the SACMA introduced sweeping reforms, permitting Qualified Foreign Institutional Investors (QFIIs) to directly participate in the Saudi market. Furthermore, integration with three prominent emerging market indices—MSCI, FTSE Russell and S&P—accompanied the reforms.[6] These reforms yielded tangible improvements, such as enhancing the overall stock market performance (Almutiri, 2020). Moreover, the liberalisation of the Saudi stock market was associated with positive outcomes, including improved price discovery, reduced bid–ask spreads and decreased high–low price volatility (Sharif, 2019). Despite the substantial impact of these events on the Saudi capital market, there is a notable gap in existing empirical evidence regarding mutual fund performance during these SMEs. In summary, the present study aims to bridge

[6] More details about financial reforms are presented in the literature review.

existing literature gaps by accounting for methodological issues, conducting a direct comparison between active and passive fund performance, and contrasting mutual fund performance during a long sample period to that during SMEs.

Another advanced and crucial area of research as regards active mutual fund performance involves the study of performance persistence. This area of study investigates whether significant performance can truly be attributed to genuine stock-picking skills or is merely a result of pure luck. To illustrate, given that numerous mutual funds operate within a country, possibly, a small subset of these funds experiences consecutive and substantial outperformance because of sheer luck. As demonstrated by Malkiel (2020), luck plays a crucial role in active fund performance, as consecutive significant performance outcomes attributable to luck may occur. Therefore, it is essential to assess the skills of managers while accounting for the potential persistence of luck. To effectively recognise managers who possess skill and those who rely on luck, and to account for the potential non-normal distribution of individual mutual fund performance, the application of the bootstrap statistical technique is imperative (Kosowski et al., 2007). This technique enables an investigation into the significance of funds' alphas while simultaneously controlling for luck-based performance.

Some studies, such as those of Avramov et al. (2020) and Kosowski et al. (2006, 2007), have offered empirical evidence in support of the presence of skilled fund managers. However, others such as Cuthbertson et al. (2008) and Fama and French (2010), have provided contrasting evidence because they failed to find support for the presence of skilled managers. Among the limited studies conducted, none has yet employed the bootstrap statistical technique to assess performance persistence specifically within active mutual funds in Saudi Arabia. Addressing this gap is a central objective of Chapter 6 in this study. After a comprehensive evaluation of mutual fund performance, the subsequent step involves identifying the pivotal factors that may significantly affect the measured performance.

Saudi Arabia's equity mutual funds operate in a very distinct market. Central to this unique context is the significant dominance of individual traders in market trading, a phenomenon that is likely to have substantial effects on fund performance. Since the Saudi market's unique attribute is its marked reliance on individual traders, they wield a significant role in shaping equity market behaviour. These traders tend to make trading decisions based on subjective and noisy expectations, rather than strictly adhering to fundamental economic factors. This divergence from rational decision-making often leads to asset prices deviating from their intrinsic values as underscored by seminal studies, such as those of Black (1986) and Shleifer and Summers (1990). Accordingly, investor sentiment is widely used to measure the noisy expectations of individual traders through a range of proxies.[7]

The significant role of individual traders on the Saudi market is evidenced in the monthly trading and ownership report from the Saudi Stock Exchange, that is, the Tadawul (2020), which revealed that individual traders accounted for an average of 82% of the monthly trading volume in 2010–2020.[8] This considerable participation profoundly influences the market, as shown by researchers such as A. Rahman et al. (2015) who identified pervasive herding behaviour among market participants across varying conditions. Moreover, the discernible influence of investor sentiment on stock volatility (Alnafea & Chebbi, 2022) and aggregate market returns (Altuwaijri, 2016) underscores the potency of this factor within the Saudi market.

[7] Investor sentiment and its proxies are discussed in detail in Chapter 3 (Subsection 3.7.1).

[8] This report revealed the significant presence of individual traders within the Saudi market, which stands in stark contrast to more developed markets. For example, in developed markets, such as the US and Europe, individual traders account for barely 10% and 5% of the total trading volume, respectively (Adinarayan, 2021).

Although mutual fund performance varies from market performance owing to the expertise of professional managers, an interplay still may emerge between the investor sentiment of individual traders and mutual fund performance. This possibility is reinforced by the remarkable participation of individual traders in the Saudi market, who have the capacity to induce market fluctuations. This alignment of factors raises the possibility of a discernible link between investor sentiment and the performance of both active and passive funds. Despite the evident significance of this factor in the Saudi equity market, prior research has largely disregarded the potential impact of individual traders' noisy expectations, encapsulated as investor sentiment, on mutual fund performance. This critical gap is addressed in Chapter 7 of this thesis, which explores the intricate relationship between investor sentiment and the performance of mutual funds in the Saudi Arabian context. Last, recognising the contemporary global landscape defined by the far-reaching effects of the COVID-19 pandemic on economic activities and equity markets, a dedicated separate chapter (Chapter 8) will be devoted to comprehensively investigating the pandemic's potential impact on mutual fund performance in the Saudi Arabian context.

The remainder of this chapter is structured as follows. The next section outlines the research objectives. Then, in Section 1.3, these are developed into research questions, on the basis of which the study's hypotheses are developed later. Section 1.4 describes the research methodology employed. Section 1.5 elaborates on the study's dual contributions—its advancement of knowledge and its practical implications. The last section describes the overarching structure of the thesis and presents a brief summary of each chapter.

1.2 Research Objectives

The thesis comprehensively investigates the performance of active mutual funds in Saudi Arabia during 2010–2020 and compares it with that of passive mutual funds. The findings of this investigation yield fresh insights into mutual fund performance, thereby contributing empirical evidence to both the scholarly literature and industry practitioners in the Saudi Arabian context. Thus, this study has the following specific objectives:

1. Rank asset pricing models and identify the most efficient model that measures active mutual fund risk-adjusted performance in Saudi Arabia.
2. Conduct a comprehensive investigation of active and passive mutual fund performance in Saudi Arabia that involves
    - investigating the benchmark-adjusted performance and the risk-adjusted performance of active and passive funds;
    - comparing the performance of active and passive funds during the overall sample period with that during periods of SMEs;
    - comparing the performance of active funds with that of passive funds;
    - exploring the potential impact of selecting different benchmark indices as proxies for market returns on the inference of mutual fund performance; and
    - examining the market timing skills of active fund managers.
3. Examine the risk-adjusted performance persistence of individual active funds in Saudi Arabia.
4. Investigate the potential influence of variables such as investor sentiment, oil price volatility, adherence to Islamic law, management expense ratio, fund flows, fund age and fund size on both unadjusted return performance and risk-adjusted return performance of active and passive funds.
5. Investigate the potential effects of the COVID-19 outbreak on both unadjusted and risk-adjusted performance of active funds.

1.3 Research Questions

Question 1.A: Do multi-factor pricing models, namely, the Fama–French three-factor model (FF3FM), the Fama–French five-factor model (FF5FM), the Fama–French–Carhart four-factor model (FFC4FM) and the FFC6FM measure the performance of active mutual funds more accurately than the single-factor model (SFM)?

Question 1.B: Does the FF5FM measure the performance of active mutual funds more accurately than the FF3FM?

Question 1.C: Does the FFC6FM measure the performance of active mutual funds more accurately than the FFC4FM?

Question 2.A: To what extent do active and passive funds in Saudi Arabia perform against three different benchmark indices: TASI, MSCI-SADI and S&P-SADITR?

Question 2.B: How did active and passive funds perform during SMEs compared with their performance during the overall sample period?

Question 2.C: To what extent did active funds perform compared with passive funds?

Question 2.D: Does the selection of a benchmark index as a proxy of market returns change the inference of mutual fund performance?

Question 2.E: To what extent can active mutual funds in Saudi Arabia time the market?

Question 3: Does the risk-adjusted return performance of individual active mutual funds persist in the Saudi market? (Can the risk-adjusted return performance of individual active mutual funds be attributed to managerial skills?)

Question 4: Are the return performance of active funds and of passive funds in the Saudi equity market affected by factors such as investor sentiments, oil price volatility, management fees, flow, age of fund, size of fund and compliance with Islamic law (shariah)?

Question 5: Did the COVID-19 outbreak affect the unadjusted return performance or the risk-adjusted return performance of active mutual funds?

1.4 Research Methodology

This study adopts a deductive reasoning approach to investigate hypotheses and address the research questions. Accordingly, the formulation of hypotheses is grounded in related theories, and then quantitative methods are used to validate or refute these hypotheses.

The use of quantitative research methods is justified by their effectiveness in addressing the questions of this study. Quantitative research yields high-quality results characterised by validity and reliability (Weir, 2013). Given the nature and extensive volume of raw numerical data, the quantitative methodology is particularly suitable. The quantitative approach involves several key procedures. Initially, secondary data are collected from various databases. Then, invalid entries are eliminated, the values of essential variables are computed and data are organised using Excel spreadsheets. Subsequently, suitable econometric models are employed, and a range of statistical tests are conducted using Stata to either accept or reject the hypotheses (see details in Chapter 4).

1.5 Contribution of This Study

1.5.1 Contribution to Knowledge

Prior studies have focused extensively on mutual fund performance in developed markets. Thus, emerging markets, in general, and the Saudi Arabian market, in particular, have received scant research attention. The main objective of the current research is to enhance knowledge in this field by providing evidence from Saudi Arabia for an in-depth understanding of mutual fund performance, performance persistence and potential factors that influence this measured performance. This study contributes to the body of knowledge in several aspects:

First, this study adds new empirical evidence and thus contributes to resolving the academic debate regarding mutual fund risk-adjusted performance and managerial skills from the Saudi Arabian market. A main assumption of the EMH is that no investor can persistently outperform the market without additional risks owing to the perfect rationality of all market participants. The existing body of literature has substantially focused on the US and other developed markets. However, it is crucial to acknowledge that the conclusions drawn from these markets are not applicable to the Saudi Arabian financial market. This is primarily because the Saudi market exhibits unique characteristics that distinguish it from other markets, thereby presenting distinctive opportunities and challenges for mutual fund managers.

Second, this study makes significant contributions to the understanding of the performance of Saudi mutual funds by addressing key methodological gaps in the literature. First, it tackles the issue of benchmark index choice by utilising and comparing fund performance against three indices: TASI, MSCI-SADI and S&P-SADITR. This approach rectifies the limitation of using TASI alone, ensuring a more reliable assessment of mutual fund performance. Second, the research introduces a more advanced asset pricing model, the FFC6FM, to estimate risk-adjusted performance, potentially making it the first study on Saudi Arabia to examine the efficiency of multi-factor models in examining mutual fund returns. This approach enhances the precision of risk-adjusted performance measurement, providing a new perspective on fund evaluation. Last, the study addresses the often-overlooked survivorship bias by including both existing and liquidated funds in the analysis, thereby producing survivor-bias-free evidence.

Third, the direct comparison between active and passive fund performance provides more valuable insights into the two competing investment strategies in the Saudi market. Frino and Gallagher (2001) have criticised the formal practice of measuring active fund performance against benchmark indices (passive returns) because indices are not investable instruments (paper portfolios) and do not incur any expenses. Consequently, unlike the formal practice of comparing active fund performance with the returns of benchmark indices, the comparison of active with passive fund performance provides new evidence with a realistic approach of the most feasible investment strategy in Saudi Arabia.

Fourth, this thesis extends the understanding of how Saudi Arabian mutual funds perform during SMEs. Their performance could differ during financial crises or major financial reforms. For example, Moskowitz (2000) argued that investors' marginal utility of wealth increases during market downturns, implying that fund managers may add value for investors during market downturns. Empirical evidence has validated this argument and confirmed that mutual funds add value for their investors during market downturns (Kosowski, 2011). Moreover, the 2015 financial reforms have resulted in improvement in the general performance of the Saudi stock market (Almutiri, 2020), the stock price discovery process (valuation) and ask–bid spreads (liquidity), and in a decrease in high–low price volatility (Sharif, 2019). The analysis of Saudi Arabian mutual fund performance during the financial crises of 2014–2016 and 2019–2020, and before and after the major financial reforms in 2015 will provide understanding of the behaviour of mutual funds in terms of their performance during critical periods.

Fifth, this thesis provides new evidence on the persistence of mutual fund performance in Saudi Arabia, and thus contributes to resolving the ongoing debate in the finance domain regarding the skills of fund managers. The examination of mutual fund performance persistence considers the crucial question of whether an individual fund's significant performance is a result of skilful stock-picking or mere chance. This study employs a bootstrap statistical technique on the entire spectrum of available funds, utilising the latest data to distinguish genuine managerial skills while accounting for the influence of luck. Furthermore, this investigation into fund performance persistence takes into consideration the impact of the significant financial reforms in 2015. The study conducts analyses for the periods both preceding and following these reforms, which allows it to make meaningful comparisons and draw subtle conclusions.

Sixth, this research identifies new factors that affect mutual fund performance in Saudi Arabia. Given the significant involvement of individual traders in the Saudi Arabian equity market (Tadawul, 2020), coupled with empirical findings illustrating the influence of investor sentiment on the volatility of stocks (Alnafea & Chebbi, 2022) and on the overall market returns (Altuwaijri, 2016), there was an intriguing gap in the body of knowledge—that is, an absence of evidence pinpointing the influence of investor sentiment on mutual fund performance. To fill this gap, the present study sheds light on this unexplored facet, contributing a comprehension of how mutual fund performance is driven by investor sentiment in the Saudi equity market.

Seventh, this thesis contributes significantly to the body of knowledge by providing empirical evidence of the impact of the COVID-19 pandemic on mutual fund performance. While prior studies have documented empirical evidence of this impact on the overall performance of the Saudi Arabian equity market or on the performance of certain stocks (Alzyadat & Asfoura, 2021; Atassi & Yusuf, 2021; Sayed & Eledum, 2021), the specific effects of COVID-19 on mutual fund performance have not been conclusively established. This is because mutual fund performance is distinct from overall market performance, owing to the influence of professional management (Bodie et al., 2010). Managers of active mutual funds may have the potential to shield the fund's performance from the pandemic's effects. Thus, this study seeks to bridge this gap in the literature by investigating the relationship between the spread of the COVID-19 virus in the country and mutual fund performance, particularly in the context of a less diversified economy.

1.5.2 Practical Contribution

The findings on actual mutual fund performance have several practical applications. These practical applications may be of interest to mutual fund subscribers (investors), fund providers (fund managers) and policymakers.

First, the methods and findings of this study can benefit fund subscribers seeking to enhance their investment planning, analysis and strategies. Specifically, the study highlights the distinction between benchmark-adjusted returns and risk-adjusted returns, revealing that a seemingly positive benchmark-adjusted return could turn into a significant negative risk-adjusted return on considering other systematic risk factors. Advanced asset pricing models, such as FF5FM and FFC6FM, can help investors choose the most suitable model for assessing mutual fund risk-adjusted performance in the Saudi Arabian context. Moreover, exploring mutual fund performance during SMEs enables investors to capitalise on the fluctuating nature of active fund performance, incorporating predictability into their strategies. In addition, investigating the effect of selecting different benchmark indices as proxies for market returns empowers investors to gauge fund performance more accurately according to their investment objectives.

Furthermore, this study breaks new ground by providing empirical evidence of active fund performance compared with that of passive funds within the Saudi Arabian context. Unlike prior studies that predominantly focused on Islamic versus non-Islamic perspectives, this study examines the active versus passive perspective, offering investors insights into two competing investment strategies. The lack of empirical evidence that supports persistent active fund performance in the Saudi market implies that significant risk-adjusted returns may be attributed to luck rather than skill. The analysis of persistence in individual performance would guide investors in distinguishing significant performance that is attributable to genuine managerial expertise from that attributable to mere chance.

Second, the methods and results of the study may assist mutual fund providers (fund managers) in developing their product plans and investment strategies. The comparison of active funds may encourage mutual fund providers to expand their products with specific investment strategies, especially those that show outstanding performance. Furthermore, understanding how investor sentiment and irrational behaviour affect fund performance may prompt Saudi fund providers to develop their sentiment indicators in order to aid their investment strategies. Last, the study also notifies fund providers of fund-specific factors affecting their performance, such as the impact of fund size on mutual fund performance. If positive and significant effects are found, fund providers may consider merging small funds to form larger ones.

Last, the findings of this study have implications for policymakers who monitor operations and reforms within the Saudi capital market. The mutual fund industry has a key role in the financial system, given that it manages investors' savings and the portfolios of pension and semi-government funds. The study's methods and findings can assist policymakers in promoting standards and techniques for monitoring the mutual fund sector and enhance transparency. The analysis of mutual fund performance before and after the financial reforms of 2015 would provide the SACMA with evidence about the effectiveness of their reforms on the mutual fund industry. This information will help policymakers in setting future reforms and regulations. Moreover, mutual fund performance is crucial for government agencies, as returns in the equity market guide them in pricing future debt issuances.

1.6 Thesis Structure

This chapter has provided a background of this research in the finance field. It described the research problem and the need for this research. It also specified the research objectives and questions. Furthermore, it described the contribution to knowledge and the practical contribution of this study. The thesis comprises another eight chapters as follows:

Chapter 2: An Overview of the Economy, the Securities Exchange Market and the Mutual Fund Industry of Saudi Arabia. This brief chapter assists readers to understand the economic environment and governance status under which Saudi Arabian mutual funds operate. It provides an overview of the Saudi Arabian economy, the historical development of the financial market and the mutual fund industry in Saudi Arabia.

Chapter 3: Literature Review. This chapter reviews prior academic studies on mutual funds in developed markets, emerging markets and in Saudi Arabia to identify potential research gaps. It also reviews the research designs and methods of these studies in order to determine the appropriate methods to be applied in the current study.

Chapter 4: Research Methodology. This chapter defines the variables, describes the theoretical background of variables, and presents the statistical tests and econometric models that are applied to achieve the research objectives and to answer the research questions. The chapter also explains the scope of the study and data collection methods.

Chapter 5: Mutual Fund Return Performance. This chapter aims to conduct a comprehensive investigation of the performance of active and passive mutual funds in Saudi Arabia in order to address several key objectives. First, it investigates the benchmark-adjusted and risk-adjusted performance of both active and passive funds. It then proceeds to compare fund performance during the overall sample period to that during specific periods of SMEs.

Furthermore, it undertakes a detailed evaluation to compare the performance of active funds with that of passive funds, thus shedding light on funds' investment strategies. It also explores the potential impact of selecting different benchmark indices as proxies for market returns on the inference of fund performance. Last, the chapter thoroughly examines the market timing skills exhibited by active fund managers in Saudi Arabia.

Chapter 6: Analysis of Mutual Fund Return Performance Persistence. This chapter focuses on the persistence in active mutual fund performance, investigating whether the potentially significant alpha of active mutual funds in Saudi Arabia is attributable to the genuine stock-picking skills of managers or stems from the persistence of good luck.

Chapter 7: Impact of Investor Sentiment on Equity Mutual Funds Performance. This chapter expands the literature by examining a new factor that potentially influences mutual fund performance—investor sentiment. It studies the influence of this factor, along with other factors, on mutual fund performance within the Saudi Arabian market.

Chapter 8: Impact of COVID-19 on mutual fund performance in Saudi Arabia. This chapter aims to identify the potential impact of both the increase in new confirmed cases of COVID-19 and fatalities on the unadjusted return performance and risk-adjusted return performance across equity mutual funds.

Chapter 9: Conclusion and Limitations of the Study. This concluding chapter summarises the thesis. It provides a summary and discussion of the main findings and draws connections with past empirical studies, in order to fulfil the research objectives. Building upon the current findings, the chapter describes the practical contributions and policy recommendations arising from the study. Furthermore, it explains the research limitations, offering insights into the constraints encountered during the study, and concludes with suggestions for future research.

Chapter 2: An Overview of the Economy, the Securities Exchange Market and the Mutual Fund Industry of Saudi Arabia

2.1 Introduction

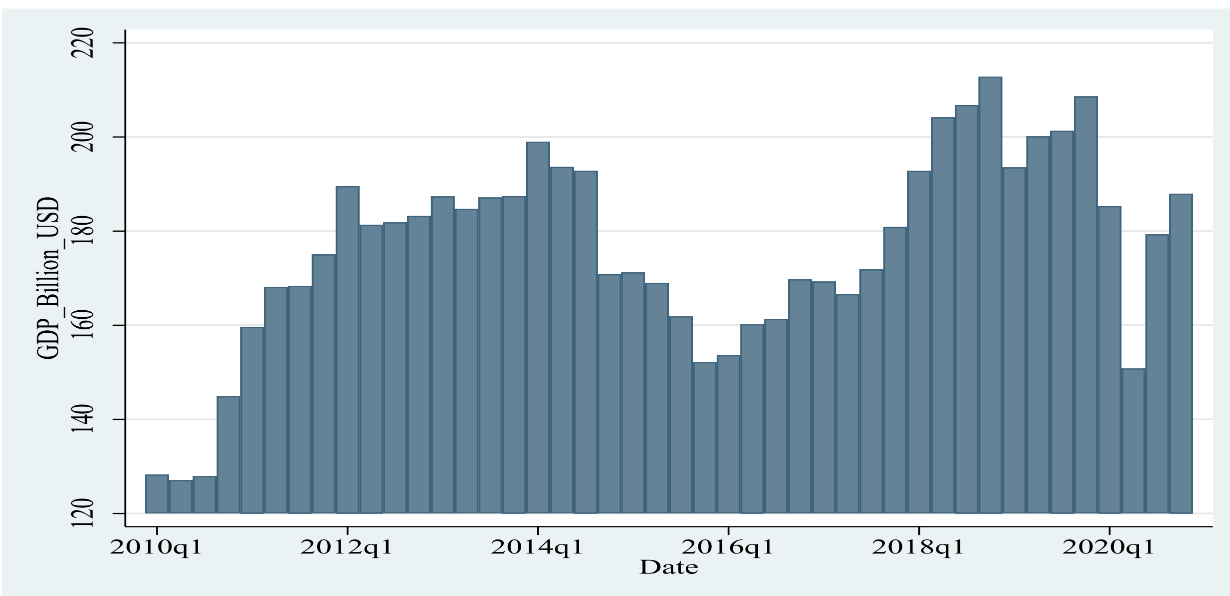
This chapter focuses on the historical development of Saudi Arabia's economy, its capital market and its mutual fund industry. It assists in understanding the economic environment and governance status under which Saudi mutual funds operate. Hence, this chapter is organised into three subtopics as follow. Section 2.2 describes the size and the main drivers of the economy of Saudi Arabia. Section 2.3 provides an overview of the historical development of the Saudi market, of the growth of equity market capitalisation and of financial crises in this market. Moreover, this section highlights the unique characteristics that distinguish the Saudi stock market from other stock markets, such as the dominance of individual traders, the high government ownership and the high volatility. Section 2.4 reviews the historical emergence of, and the regulations applicable to, Saudi mutual funds. It also focuses on fluctuations in the size of the overall mutual fund industry.

2.2 The Economy of Saudi Arabia

The Saudi economy is one of the fastest growing economies in the world. Saudi Arabia is a member of the G20 group and has the largest economy in the Arab world and the Middle East (The World Bank, 2021). Figure 2.1 shows that its gross domestic product (GDP) grew from USD128 billion in the first quarter of 2010 to USD188 billion in the fourth quarter of 2020. The GDP slid from about USD200 billion in the first quarter of 2014 to USD154 billion in the first quarter of 2016. This steep decline was due to the collapse in oil prices following the oil price competition between the Saudi Government and the Russian Government during that period. This collapse in oil prices also caused severe declines in the Saudi Arabian equity market between 2014 and 2016. Again, there was a sharp decline in GDP in the fourth quarter of 2019 and in 2020 following another oil price competition between the Saudi Government and the Russian Government and this decline was later exacerbated by the occurrence of the COVID-19 pandemic. Recently, the Saudi Government has launched Vision 2030, which aims to reduce the country's dependence on oil, diversify the economy and increase private sector participation in the national economy. However, oil revenues still played a significant role in the Saudi economy in 2020.

Figure 2.1

Saudi Arabia Quarterly GDP: Q1 2010 to Q4 2020



Note. The bar chart shows Saudi Arabia's quarterly gross domestic product (GDP) from the first quarter of 2010 to the fourth quarter of 2020 in billion USD. The researcher imported data from the database on the GDP and national accounts maintained by the General Authority for Statistics (2022) and converted the values from Saudi Arabian Riyal (SAR) to USD (1 USD = 3.75 SAR). The Stata software was used to generate this figure.

The Saudi Ministry of Finance depends heavily on oil revenues to subsidise most aspects of economic development and activities. Saudi Arabia has been the largest crude oil exporter globally since 1980 and is a founder and a permanent member in the Organisation of the Petroleum Exporting Countries. Crude oil exports and petrochemicals are the main drivers of the Saudi economy (Albassam, 2015). According to the annual economic reports and statistics published by the Saudi Central Bank (SAMA, 2020), on average, oil revenues have comprised 76% of the Saudi annual budget incomes for the past 40 years. Crude oil prices have extreme effects on economic growth and the government's fiscal spending as oil revenues are used to finance new capital projects and advanced technologies. As a result, there is a strong positive relationship between oil revenues and the real GDP in the short and long terms (Alkhathlan, 2013).

This brief introduction of the Saudi economy is important to understand the behaviour of the Saudi equity market. Most industries in this market are very sensitive to government spending. The private sector's contributions to economic growth in the Gulf Cooperation Council (GCC) countries is less than in developed countries and much less than in other countries with a similar economic structure (Hertog, 2013). The economy of Saudi Arabia relies heavily on the government's patronage and support. For instance, the public sector employs almost two-thirds of Saudi citizens (Hertog, 2018). Moreover, the Saudi Government's fiscal spending has a significant and positive impact on non-oil sectors in both the long term and short term (Hasanov et al., 2022). Investors in the Saudi equity market perceive growth in government fiscal spending and economic development as an increase in the potential operating incomes of local corporations.

2.3 Saudi Equity Market: Development, Crises and Characteristics

The Tadawul is the largest securities exchange in the Middle East. By 2020, there were 203 publicly traded companies with a total market capitalisation exceeding USD2.5 trillion

(Tadawul, 2020). The Saudi exchange market is divided into 20 industries: energy; materials; capital goods; commercial and professional services; transportation; consumer durables and apparel; consumer services; media and entertainment; retailing; food and staples retailing; food and beverages; health care equipment and services; pharma, biotech and life science; banks; diversified financials; insurance, software and services; telecommunication services; utilities; real estate investment trusts (REITs); and real estate management and development. This section focuses on the historical development of the Saudi equity market, past financial crises and this market's unique characteristics.

2.3.1 Saudi Equity Market: Historical Development

Several supervisory authorities have developed the Saudi equity market over the past 40 years. It grew rapidly from a small unofficial market between the 1950s and the 1980s to the largest market in the Middle East. It emerged spontaneously and informally with a few companies during the 1950s. Investors traded their securities manually with their close connections. In the 1980s, the government legislated basic regulations for the market and assigned its supervision to three authorities. The Ministry of Commerce was in charge of the formation of new companies, the conversion of firms to joint stock companies and initial public offerings (IPOs); the Ministry of Finance was responsible for setting objectives and policies; and the SAMA commanded the operational and functional management of the market. However, the Saudi stock market faced serious challenges, such as the lack of an organised legal framework, non-specialist agents that emerged to deal with shares, board members' and founders' large percentage of ownership of issued shares, the limited understanding of stock market operations and transactions among most Saudi citizens and the restriction that citizens of other Arabian Gulf countries could invest in Saudi stocks only through Saudi agents (Ramady, 2010). In 2001, SAMA introduced Tadawul[9]—an electronic, accurate system for clearing and settlement—which attracted more Saudi citizens to stock trading. The SACMA was officially established in 2004 to take over the supervision of the market from SAMA, and the Council of Ministers approved the formation of the Saudi Stock Exchange (i.e. Tadawul), as a joint stock company in March 2007 (Ramady, 2010).

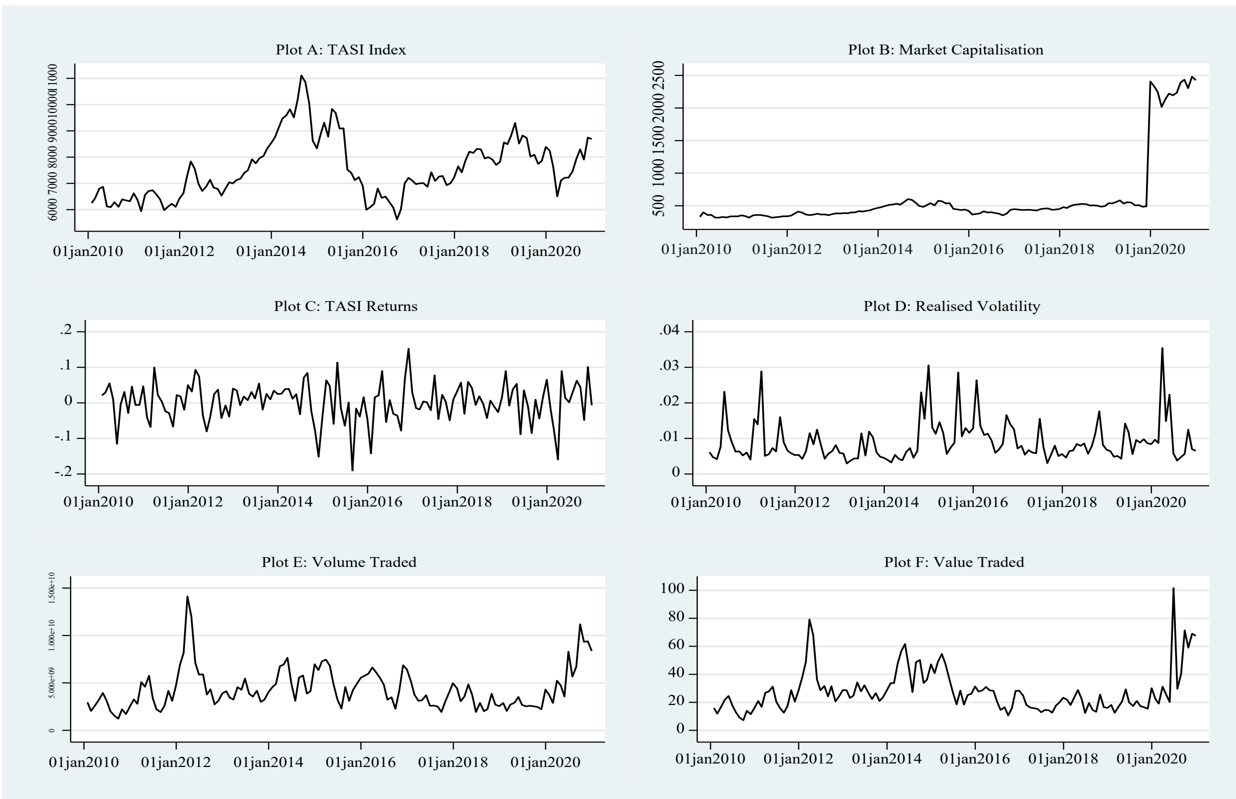
TASI is the main index of the Saudi equity market. A free-float methodology is used for index calculation, and data on all traded firms are included for this calculation. Figure 2.2 presents six indicators of the Saudi capital market during the study period (from January 2010 to December 2020). Plot A shows fluctuations in the price level of TASI: TASI peaked at 11,112.12 points in August 2014 and sank to a low of 5,623.34 in September 2016. This major decline of more than 41% was attributed to the collapse in oil prices and a steep decease in the country's GDP. Another major fall started after mid-2019 because of the oil price competition between Saudi Arabia and Russia, which was then exacerbated by the COVID-19 pandemic. Plot B shows the market capitalisation in billion USD. From January 2010 to November 2019, the capitalisation fluctuated between USD317.55 billion and USD602.25 billion. However, in December 2019, there was a structural change in market capitalisation as the IPO of the state-owned oil company, the Saudi Arabian Oil Group (Aramco) overshadowed every IPO in history with a value of USD1.88 trillion. After the listing of Aramco, the market capitalisation averaged around USD2.5 trillion. Plot C presents the time series of TASI returns. TASI achieved the highest returns of 15.21% in November 2016, which declined to −19.01% in August 2015, with an average return of 0.265%. As Plot D, which illustrates the realised volatility of market returns shows, there were significant spikes in realised volatility during the financial crisis between September 2014 and September

[9] Initially, Tadawul was the name of the clearing system, and it was then used as the title of the Saudi Stock Exchange.

2016 and during that caused by the COVID-19 pandemic. Last, Plots E and F show the monthly volume traded and value traded, respectively. On average, TASI processed more than 104 billion transactions monthly in 2010–2020 valued, on average, at USD28 billion.

Figure 2.2

Key Indicators of the Saudi Arabian Capital Market, January 2010 – December 2020



Note. This figure shows the main indicators of the Saudi Arabian stock market: TASI price level (Plot A), market capitalisation in billion USD (Plot B), TASI returns (Plot C), realised volatility (Plot D), volume traded (Plot E) and value traded in billion USD (Plot F). All the time series are plotted using monthly data for January 2010 – December 2020. The data were obtained from the Refinitiv Datastream database, and the Stata software was used to generate the figure.

2.3.2 Saudi Equity Market Financial Crises

The Saudi stock market has grappled with four financial crises since 2000: the financial crises of 2006, 2008–2009, 2014–2016 and 2019–2020. Among these, the financial crisis of 2006 stands out as the most devastating one the Saudi stock market has ever experienced. According to

Alkhaldi (2015), several significant events and conditions paved the way for this crisis. First, in the aftermath of the 9/11 attacks, global instability prompted many affluent Saudi families to repatriate their wealth to Saudi Arabia, leading them to invest in the equity market. Second, the SAMA's introduction of the new clearing system (i.e. Tadawul) in 2001 facilitated trading for inexperienced individual traders, attracting a substantial number of them to the market. Third, during the upward market trend, media narratives amplified stories of overnight wealth accumulation, enticing even more inexperienced individual traders into the stock market. In addition, the inexperienced SACMA, established in 2004, failed to intervene against price manipulators.

The frenzy reached a peak as ordinary people liquidated their assets, including homes, cars and personal valuables, with thousands taking bank loans to speculate in the market (*Saudi Gazette*, 2017). In the midst of this speculative mania, TASI skyrocketed by 740% within three years, soaring from 2,500 points at the beginning of 2003 to approximately 21,000 points in February 2006. At its zenith, over 50% of Saudi adults were invested in the stock market (Alkhaldi, 2015). However, as no additional funds were available to sustain the bubble, the stock market plunged to around 7,000 points at the end of 2006, marking a staggering 67% decline. The estimated losses amounted to USD530 billion. Throughout 2007, the market experienced a brief respite, fluctuating between 7,000 and 10,000 points. Unfortunately, the global financial crisis of 2008–2009 hit the Saudi equity market severely. In March 2009, the Saudi stock market reached its nadir at about 4,000 points, representing a 60% fall from the close of 2007. In subsequent years, the Saudi capital market witnessed two additional financial crises, namely, in 2014–2016 and 2019–2020.[10]

[10] These crises are discussed in Chapter 3 and are included in the analysis presented in this thesis.

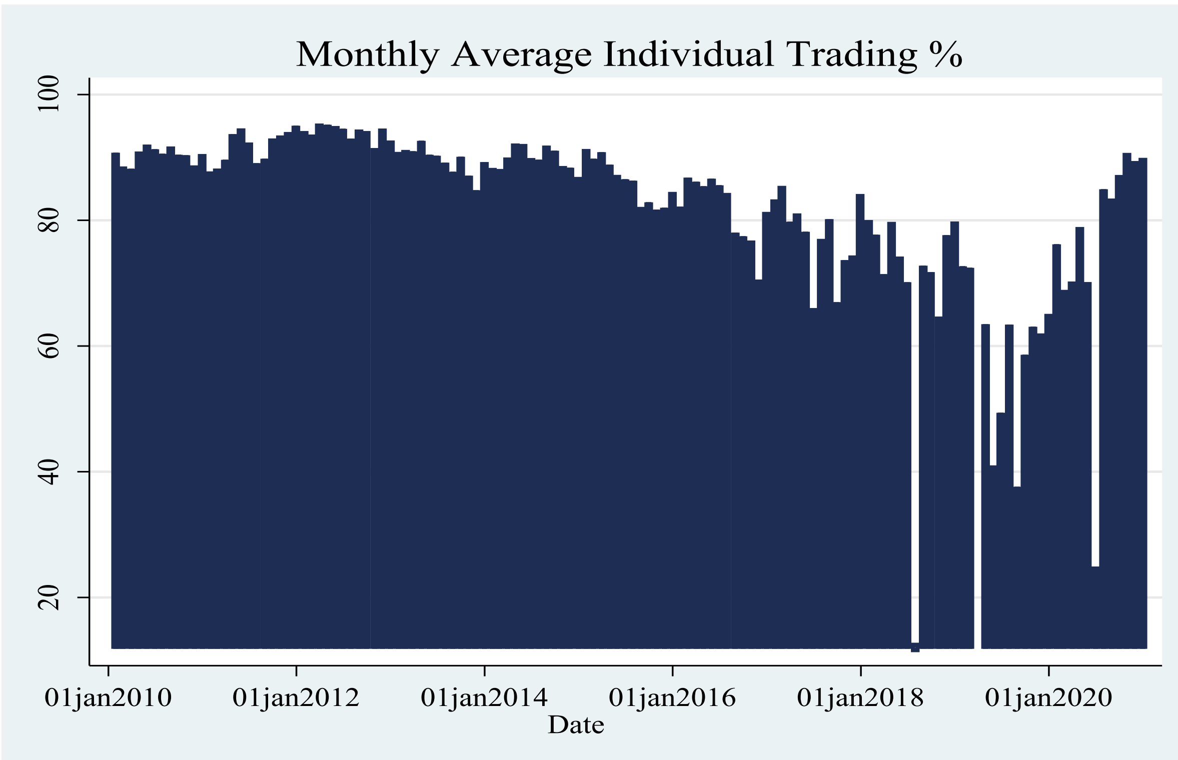
2.3.3 Unique Characteristics of the Saudi Equity Market

The Saudi market possesses distinct characteristics that set it apart from other markets. One is the dominance of individual traders in trading activities, exhibiting weak-form inefficient behaviour. Moreover, the market lacks advanced risk-management instruments, has high government ownership and experiences significant volatility.

Foremost among these characteristics is the dominance of individual traders, a pivotal factor shaping the Saudi market. According to Tadawul (2020) monthly trading and ownership reports, and as depicted in Figure 2.3, individual traders contribute significantly to the market's trading volume. From January 2010 to December 2020, their average trading volume constituted approximately 82% of the total. In Saudi Arabia, individual traders exhibit remarkable activity in the equity market, executing the majority of stock transactions. This trend contrasts sharply with the dominance of institutional investors observed in developed markets. These seemingly 'irrational' traders demonstrate increased activity during bullish–bearish market phases, attracted towards stocks that have recently experienced significant price appreciations (Alshammari & Goto, 2022). On average, the data reveal a notable shift in individual trader behaviour following the introduction of the 2015 financial reforms. Prior to these reforms, individual traders accounted for more than 91% of monthly trading, on average. However, post July 2015, this figure decreased to 73%. Despite this decline, their participation remains exceptionally high compared with the participation of their counterparts in developed stock markets. In essence, these statistics underscore the pivotal role of individual traders in shaping the Saudi market behaviour.

Figure 2.3

Monthly Average Percentage of Trading Volume by Individual Traders as a Proportion of Overall Trading Volume in the Saudi Equity Market, January 2010 to December 2020



Note. Data were collected from Tadawul reports on monthly stock market ownership and trading activity (Tadawul, 2020). Then, the average monthly volumes bought and sold by individual traders as a percentage of the total volume traded, by investor type were calculated, and the data were organised in time-series form. The Stata software was used to generate the figure.

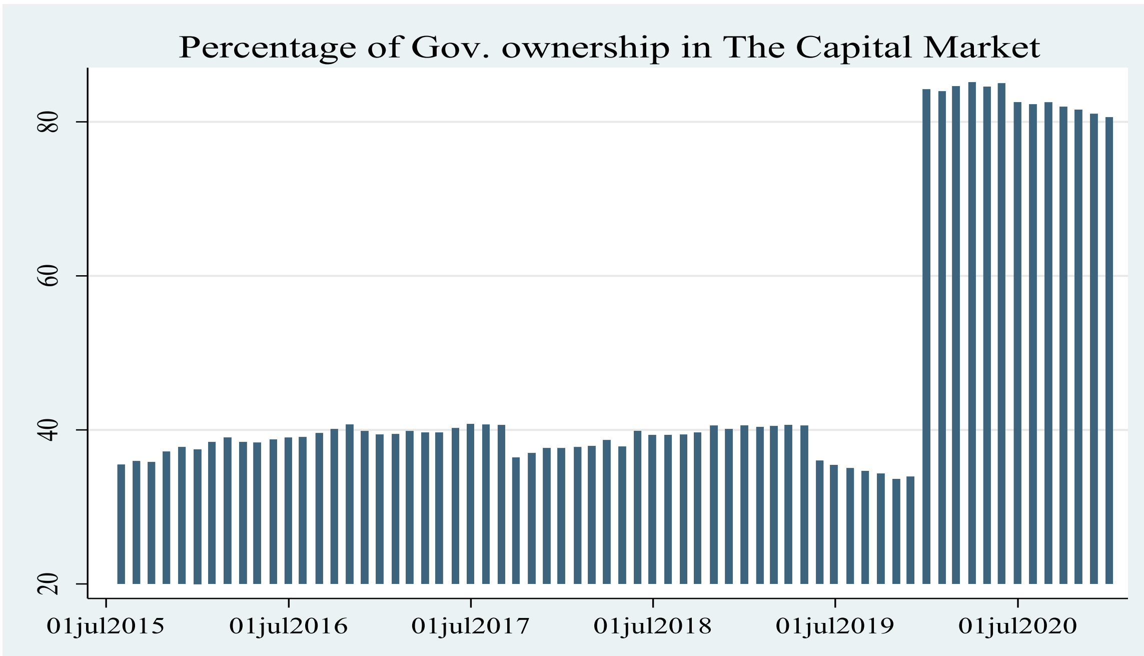
Second, the Saudi market exhibits weak-form inefficient behaviour, as evidenced by empirical studies. In this regard, Al-Ajmi and Kim (2012) revealed that the variance ratio-joint sign test decisively rejects the hypothesis that the Saudi Arabian market adheres to a random walk pattern in daily and weekly returns. Furthermore, Lamouchi (2020), who investigated the long memory of Saudi daily returns and volatility, utilising an autoregressive fractionally integrated moving average model, uncovered evidence supporting the existence of prolonged memory in the Saudi stock market. In addition, Syed and Bajwa (2018) employed an event study approach to demonstrate that substantial abnormal returns can be realised around expected days of earnings announcements. In a related aspect, the absence of advanced risk-management instruments, such as derivatives, implies that even well-informed investors lack access to arbitrage prices.

Third, the Saudi Arabian equity market is characterised by substantial government ownership, a feature that sets it apart from developed markets. The Public Investment Fund—the sovereign wealth fund—manages a staggering USD600 billion in government assets. It establishes major corporations across critical sectors and then sells part of its holdings, thereby fostering corporate governance. As depicted in Figure 2.4, the percentage of Saudi Government ownership in the equity market surged from an average of 37% in 2015 to an average of 83% in 2020. This notable increase, particularly in December 2019, was primarily driven by the listing of Aramco, in which the government owns 95% of the total issued shares. According to Hertog (2010), GCC state-controlled firms enjoy various government advantages, including access to cheap energy and feedstock. Individual investors perceive state ownership as value-enhancing owing to preferential financing and implicit government guarantees, which increases their inclination to trade in state-controlled stocks (Ding & Suardi, 2019). The significant percentage of government ownership in the overall issued stocks also has a notable impact on the equity market dynamics. It results in a decrease in the proportion of free-float shares of corporations.[11] A low proportion of free-float shares may empower individual traders to exert greater influence on stock prices, thereby strengthening the role of investor sentiment in shaping the trajectory of the Saudi market.

[11] Floating shares are shares available for trading on any given day.

Figure 2.4

Percentage of Saudi Government Ownership in the Equity Market Relative to Total Issued Stocks, July 2015 to December 2020



Note. The bar chart shows the percentage of Saudi Arabian Government ownership to the overall issued stocks in the equity market from July 2015 to December 2020. This chart was formed using data imported from Tadawul (2020) reports on monthly stock market ownership and trading activity. The Stata software was used to generate the figure.

Fourth, the Saudi market stands out for its heightened volatility in comparison to other markets. This increased volatility can be attributed to several factors. Alsukran (2005) linked the sharp fluctuations in stock prices to the dominance and behaviour of individual traders. Unlike institutional investors who base their trades on fundamental analysis and economic factors, individual traders often engage in speculative operations driven by arbitrary considerations, thereby contributing to market volatility. Another significant factor influencing the heightened volatility in the Saudi market is its heavy reliance on oil revenues to subsidise the national economy. This dependency establishes a strong correlation between oil market volatility and the stock market volatility.

2.4 Mutual Fund Industry in Saudi Arabia

The regulatory framework for investment funds in Saudi Arabia underwent significant development over various phases. While formal legislation by the SAMA did not materialise until 1993, the National Commercial Bank had already set a precedent by establishing the country's first mutual fund in December 1979, known as the AlAhli Short-Term Dollar Fund. Following the success of this initiative, other Saudi banks followed suit, creating their own mutual funds for diverse investment purposes (Aleqtisadiah, 2011). As of 2020, the total AUM of all public investment funds in Saudi Arabia amounted to approximately USD56 billion (Capital Market Authority, 2020). It is important to note that SAMA oversaw the mutual fund industry from 1993 until 2004 when the SACMA was established and assumed regulatory responsibilities.

Table 2.1 illustrates the fluctuating size of all investment mutual funds in Saudi Arabia during 2010–2020, detailing both the number of funds and their AUM. Over this period, there was a general doubling in the size of all mutual funds, which increased from USD25.2 billion to USD55.9 billion. Despite this overall growth, there were notable fluctuations in the AUM of funds according to investment type. Specifically, equity and balanced investment funds experienced a decline in size over the past decade, with their AUM decreasing by more than 31% and 41%, respectively. However, the contraction in the size of these funds did not affect the overall mutual fund industry, as debt instruments and money market mutual funds saw staggering growth of 7,884% and 135%, respectively, in 2010–2020. These remarkable increases in AUM were anticipated, given the extensive expansions in government debts and individual consumer loans during this period. Furthermore, the introduction of REITs into the Saudi market in 2016 played a significant role in enhancing the overall size of the mutual fund industry.

Table 2.1

Number and Total Asset Value of Public Investment Funds in Saudi Arabia, by Type of Investment

Investment type	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Equities	154	150	138	141	150	169	168	161	141	137	128
	8,260	7,101	7,464	9,184	9,489	8,803	5,985	5,595	5,513	5,511	5,659
Debt instruments	6	7	9	8	9	9	8	8	5	7	12
	58	64	170	150	171	222	226	201	136	514	4,631
Money markets	56	50	47	45	46	44	44	44	43	46	46
	15,471	13,212	14,368	16,252	17,702	16,457	15,333	19,374	16,652	28,479	36,377
Real estate	6	10	10	13	11	10	12	11	10	9	9
	415	680	690	1,102	1,327	1,181	963	2,350	2,226	2,120	2,012
Fund of funds	27	43	43	41	41	30	32	32	25	25	25
	714	724	728	746	757	727	689	770	773	757	596
Balanced	2	2	3	2	2	2	2	2	2	2	2
	24	31	17	35	33	25	22	20	19	17	14
Other	16	10	6	4	4	3	8	8	7	10	10
	302	75	19	30	29	15	57	116	124	172	864
REITs	--	--	--	--	--	--	1	7	16	17	17
							148	970	4,387	5,085	5,772
Total	267	272	256	254	263	267	275	273	249	253	254
	25,244	21,887	23,456	27,499	29,508	27,430	22,803	29,396	29,830	42,655	55,926

Note. The table shows the number (above) and the asset value (below) in million USD of investment funds in Saudi Arabia by type of investment, in 2010–2020. Data were collected from the Capital Market Authority (2020) annual reports, and the asset values were converted from SAR to USD (1 USD = 3.75 SAR). REITs stand for Real estate investment trusts.

Table 2.2 classifies Saudi equity funds by the geographical location of their investments, detailing both the number of funds and their AUM. On average, equity funds have allocated approximately 73% of their assets to local equities. Over the past 11 years, there has been a downward trend in the number and AUM of equity mutual funds across all geographical locations. The number of funds decreased by about 17%, declining from 154 in 2010 to 128 in 2020, with the highest number—169 equity funds—recorded in 2015. This result indicates that the number of funds that exited the market exceeded the number that entered it. In terms of AUM, there was a significant drop of more than 31%, from USD8.26 billion in 2010 to USD5.66 billion in 2020, with the peak asset value recorded at USD9.49 billion in 2014. The AUM of local, GCC and Arab equity funds decreased by approximately 20%, 17% and 45%, respectively. European and other international equity funds experienced the most substantial decrease in AUM, with reductions of about 73% and 72%, respectively.

Table 2.2

Number and Asset Value of Public Equity Investment Funds in Saudi Arabia, Classified Geographically

Geographic location of equity	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Local	--	64	60	60	71	89	96	93	85	80	72
	5,086	4,570	4,652	5,689	6,036	5,340	4,454	3,987	4,153	4,124	4,099
GCC	--	23	22	23	26	28	27	28	24	24	24
	518	405	435	567	625	804	660	518	431	432	431
Arab	--	4	4	6	6	6	6	4	3	4	4
	66	29	49	53	122	82	51	39	33	45	36
Asian	--	13	11	11	10	10	9	8	7	7	7
	298	216	225	229	210	228	184	242	172	182	232
American	--	5	5	5	4	4	4	4	3	3	3
	310	313	360	470	538	534	178	225	246	231	302
European	--	7	6	6	6	6	5	5	4	4	4
	590	492	585	732	710	733	127	184	158	142	162
Others	--	34	30	30	27	26	21	19	15	15	14
	1,392	1,076	1158	1,444	1,248	1,082	331	400	320	355	396
Total	154	150	138	141	150	169	168	161	141	137	128
	8,260	7,101	7,464	9,184	9,489	8,803	5,985	5,595	5,513	5,511	5,659

Note. The table shows the number (above) and asset value (below) in million USD of equity investment funds during 2010–2020 in Saudi Arabia classified geographically. The data were imported from the annual reports of the Capital Market Authority (2020), and asset values were converted from SAR to USD (1 USD = 3.75 SAR).

2.5 Chapter Summary

This chapter provided an overview of the development and structure of the Saudi Arabian economy, capital market and mutual fund industry. It offers insights into the economic environment and governance conditions shaping the operation of Saudi mutual funds. Saudi Arabia is among the world's top 20 largest economies and is heavily reliant on oil revenues to subsidise various aspects of economic development and activities. The chapter discussed the evolution of the Saudi capital market, the financial crises it has experienced and the distinctive features that characterise this market. The third section focused on the historical emergence of, and the regulations governing, mutual funds in Saudi Arabia. It shed light on the fluctuations in the overall size of the mutual fund industry, providing a comprehensive understanding of the industry's trajectory. The following chapter, the literature review, critically examines studies on mutual fund performance and theoretical frameworks, providing a solid foundation for the subsequent discussions in this thesis.

Chapter 3: Literature Review

3.1 Introduction

The purpose of this chapter is to explore the research conducted on mutual funds and assess the implications of studying this area. To this end, a thorough review of academic studies across developed and emerging markets will be conducted. This literature review establishes the basis for understanding the current state of knowledge in this field and identifying potential research gaps. The goal is to develop pertinent research questions and hypotheses by building upon extant literature.

To guide this study, research designs and methods employed in prior studies will be reviewed and approaches appropriate to meet this study's objectives will be selected. In addition, the results, discussions and conclusions of past research will be analysed to establish connections between earlier findings and the current research, emphasising the significance of the current study's contributions. Given the broad scope of this investigation into mutual fund performance, this chapter is organised into subsections, each addressing specific aspects of mutual fund performance.

- Section 3.2 presents the background of the emergence of studies on, and the importance of studying, mutual fund performance within the academic field of finance. Empirical evidence on mutual fund performance holds a pivotal role in shaping the principles of MPT. This section discusses the perspectives of both the traditional finance school (TFS) and the behavioural finance school (BFS), highlighting their distinct views on the role of mutual fund performance.

- Section 3.3 explains the use of capital asset pricing models (CAPMs), including the SFM and multi-factor models, to measure mutual fund performance. It also reviews models developed to assess mutual fund managers' market timing ability.
- Section 3.4 reviews prior findings on mutual fund performance for active and passive funds. The review focuses on developed markets, emerging markets and then on the Saudi Arabian market.
- Section 3.5 extends the review of prior findings on mutual fund performance to encompass performance during significant market events.
- Section 3.6 covers the literature assessing the persistence of mutual fund performance, which examines whether mutual funds exhibiting superior performance can sustain this trend over time or whether such performance is attributable to chance.
- Section 3.7 reviews the factors influencing mutual fund performance across existing studies, drawing comparisons between findings in developed markets and those observed in the Saudi market.
- Section 3.8 summarises the chapter.

3.2 Traditional and Behavioural Finance Schools

This section highlights the importance of investigating mutual fund performance within the academic field. The foundational motivation for this thesis stems from the conflicting empirical evidence surrounding Markowitz's (1952) MPT. The MPT states that investors achieve the maximum expected return for a given level of risk. However, the substantial significant positive risk-adjusted returns observed in mutual funds pose a potential challenge to MPT when the fund's success is attributed to factors not encompassed by conventional diversification techniques. For instance, if a fund manager employs a distinctive investment strategy, enabling consistent outperformance of the market, this could result in positive risk-adjusted returns that remain unexplained by traditional portfolio optimisation models. This contradiction drives the need for empirical investigation of mutual fund performance.

In the academic field of finance, two main schools of thought contest for dominance in explaining the intricacies of financial markets: the TFS and the BFS. A brief exploration of their theories is essential in contextualising this investigation regarding mutual fund performance. The TFS asserts that financial markets operate rationally and efficiently. According to this perspective, asset prices reflect all available information, and investors make rational decisions when making investment choices. Conversely, the BFS challenges the assumption of consistent rationality, acknowledging that investors may not always act in a rational manner, and that rather, asset prices can be affected by psychological biases and other non-rational factors. This debate between these two schools has implications for the current study on mutual fund performance. By examining the performance of mutual funds, implications can be gained about the extent to which financial markets are efficient. Overall, this section provides a theoretical foundation for this investigation into mutual fund performance and highlights the relevance of the current research to the broader academic debate in finance.

The TFS, which emerged in the 1960s and 1970s, notably with the development of the MPT, aims to explain the asset pricing in financial markets. It draws from the expected utility theory of Von Neumann and Morgenstern (1944) and the subjective utility theory of Savage (1954), both of which advocate personal rationality in decision-making under risk and uncertainty (Gul & Akhtar, 2016). Within the TFS, various theories have been evolved to explain the functioning of financial markets. Random walk theory, developed by Malkiel (2020),[12] posits that

[12] The first edition of the book was published in 1973.

stock prices follow a random pattern and asserts that the probability of a stock price increasing is equal to its probability of decreasing. This theory suggests that stock prices are unpredictable and are independent of past fluctuations and other stock price movements. The EMH, introduced by Fama (1965, 1970), stands as a cornerstone theory in the TFS. EMH classifies market efficiency into three forms: weak, semi-strong and strong. Under weak-form efficiency, all past information about stock prices is incorporated into current prices, rendering technical and chart analyses ineffective in predicting prices. The semi-strong form of efficiency posits that all publicly available information, including past prices and economic data, is reflected in a stock's price, resulting in the inability of both technical and fundamental analyses to predict returns. Strong-form efficiency contends that all public and non-public information is factored into a stock's price, rendering ineffective any attempt to generate abnormal returns using past prices, economic and financial data or internal confidential recommendations.

In sum, the TFS theories propose that investors exhibit perfect rationality in their investment decisions and promptly incorporate any new information into asset prices. This perspective asserts that assets are consistently traded at their intrinsic value at any given moment, and no investor can consistently outperform the overall stock market without assuming additional risk. Despite certain assumptions within the TFS appearing unrealistic, particularly regarding the perfect rationality of financial markets and traders, influential economist Friedman (1953) argued that rational investors engage in arbitrage to correct any potential asset price deviation from intrinsic value. Friedman also argued that the empirical evidence, rather than the realism of assumptions, serves as the ultimate judge of a theory's predictive power. This pragmatic viewpoint underscores the importance of testing theories against real-world data to gauge their practical validity.

The BFS, which emerged in the 1980s, seeks to explain anomalies in financial markets that TFS has struggled to explain, including phenomena such as financial market bubbles, excess volatility and ethical investment decisions. Established on the concepts of Kahneman and Tversky (1979), Tversky and Kahneman's (1986) prospect theory and Tversky and Kahneman's (1992) cumulative prospect theory, the BFS posits the existence of personal bias in decision-making under risk and uncertainty. Unlike in TFS assumptions, according to prospect theory, individuals do not assign equal value to gains and losses. Instead, they weigh perceived gains more heavily than perceived losses.

The BFS has generated substantial studies that explain financial market dynamics and seriously critique the assumptions of EMH. First, Black (1986), in noise theory, DeLong et al. (1990), in their noise traders theory, and Shleifer and Summers (1990) proposed that irrational traders base their equity trades on noisy expectations rather than on pure fundamentals. This behaviour leads to asset prices deviating from their intrinsic value. Next, De Bondt and Thaler (1990) documented biases, such as constant overreactions, in the predictions of earnings per share by professional analysts of securities, which may result in misleading pricing evaluations for some investment institutions. In responding to Friedman's (1953) arguments, Shleifer and Vishny (1997) identified two reasons for the ineffectiveness of perfect arbitrage in adjusting security prices to their fundamental values. They argued that true capital-free arbitrage does not exist, and practical capital requirements may hinder arbitrageurs from executing their strategies. In addition, the presence of risk in arbitrage operations, particularly during extreme circumstances, serves as a second reason for the ineffectiveness of arbitrage. Furthermore, Lamont and Thaler (2003b) provided empirical evidence to support that not all mispricing can be arbitraged away. They showed that instances of asset mispricing in the US market, particularly among tech companies, persist for a considerable duration. This evidence challenges the argument that perfect arbitrage corrects all pricing discrepancies in financial markets.

Several seminal studies supporting BFS have presented evidence that stock prices are not random. First, by implementing fundamental analysis, Campbell and Shiller (1988, 2005) provided solid evidence that financial ratios hold predictive power for stock prices. Specifically, the price–earnings (P/E) ratio and the dividend–price ratio emerge as robust predictors of stock prices. Similarly, Fama and French (1988b) confirmed that the P/E ratio explains more than 25% of the variances of two- to four-year equity returns and about 5% of the variances of monthly or quarterly equity returns. Second, empirical evidence has been found in studies on serial correlation, which tested whether past prices can be used to predict prices. These studies have found positive autocorrelations in returns over short-term horizons and negative autocorrelations over long-term horizons in the US and 17 other countries (Poterba & Summers, 1988); significant negative autocorrelations over three- to five-year returns (Fama & French, 1988a); and top stock losers and stock winners reversing their directions every five years (De Bondt & Thaler, 1989). Last, another array of anomalies disrupts the assumption of market efficiency, including the January effect (Ritter, 1988; Thaler, 1987), the failure of the law of one price in various financial securities and closed-end mutual funds (Lamont & Thaler, 2003a; C. Lee et al., 1990) and the endowment effect and status quo bias (Kahneman et al., 1991).

In conclusion, the EMH contends that stocks are fairly priced, implying that it is impossible for fund managers to consistently achieve risk-adjusted abnormal returns. In contrast, the BFS allows the possibility of such opportunities and has presented evidence supporting their existence. The ongoing debate between these two schools of thought centres around the actual performance of mutual funds, which has become a focal point for proving their respective assumptions. Despite the assertions and empirical evidence supporting the EMH, active mutual funds still exist and continue to dominate the mutual fund industry. Consequently, the current study is motivated to explore the performance of these active mutual funds. By studying the largest equity market in the Middle East, this study aims to contribute evidence to finance theories, shedding light on the reality of mutual fund performance. In subsequent sections, academic findings from scholars representing both schools of thought across various areas of study will be reviewed in an effort to deepen the understanding of the complexity of mutual fund performance.

3.3 Efficiency of Models That Measure Mutual Fund Performance

3.3.1 Capital Asset Pricing Models

This section reviews the evolution of models used to assess mutual fund performance. Early literature predominantly employed fund-relative measures, evaluating mutual funds against their peers. However, a seminal work by Jensen (1968) highlighted the need for an absolute measure of performance. Building on Markowitz's (1952) MPT, independent contributions by Sharpe (1964), Lintner (1965a) and Treynor (1962) led to the development of the CAPM. Grounded in the relationship between the expected return of a portfolio and its systematic risk, the CAPM calculates the expected return of a well-diversified portfolio based on its systematic risk. The development of the CAPM marked a crucial step in developing models that could provide a more comprehensive and absolute assessment of mutual fund performance.

The CAPM is founded on five key assumptions. First, the model assumes that all investors are rational and risk-averse and pursue wealth maximisation. Second, it assumes decision-making processes are uniform, encompassing a single-period investment horizon and homogeneous expectations across all investors. Third, the model assumes that all securities are both marketable and divisible, ensuring a constant flow of buyers and sellers dealing in small quantities. The fourth assumption characterises investors as price takers, signifying an absence of dominant investors capable of influencing security prices. Last, the model envisions securities markets as frictionless, free from taxes, with universal access to short-selling, money lending, borrowing at the risk-free rate and devoid of transaction costs for traders. Despite the potential variance from real market conditions, these assumptions collectively underpin the core concept of the CAPM.

Assuming the empirical validity of the CAPM, Jensen (1968) derived Jensen's alpha as a measure of portfolio performance through a direct application of the CAPM. Initially, Jensen demonstrated that the CAPM could also be applied to a time-series regression test. He then argued that if a portfolio manager possesses superior forecasting ability, it will violate the second assumption of the CAPM. This violation occurs because the manager systematically selects securities that earn more than the risk premium for their level of risk, resulting in a non-zero error term ($\varepsilon > 0$) in the CAPM. Jensen addressed this issue by allowing for the possible existence of a non-zero constant in the model, ensuring a zero error term that is also serially independent. A positive (negative) constant in this modified version of the CAPM, which is termed the single-factor model (SFM), indicates the superior (inferior) ability of a manager to forecast securities prices. The SFM has gained popularity in both professional and academic circles for evaluating mutual fund risk-adjusted performance.

The CAPM, and implicitly the SFM, has encountered substantial challenges, facing both theoretical and empirical criticisms in the literature (Campbell & Vuolteenaho, 2004; Fama & French, 2004; Jensen et al., 1972; Miller & Scholes, 1972; Roll, 1977, 1978). Banz (1981) revealed a deficiency in CAPM's ability to capture the size effect. By sorting firms according to market capitalisation, Banz observed that the actual average returns on small firms consistently exceeded predictions from the model. Rosenberg et al. (1985) and Stattman (1980) further identified

CAPM's failure to account for the value effect. On grouping firms by their book-to-market equity (B/M) ratios, they found that firms with high B/M ratios consistently exhibited higher actual average returns than predicted by CAPM. This body of literature demonstrated the inadequacy of the SFM in capturing crucial risk information embedded in financial ratios. Failure to incorporate these risk indicators within the model results in underestimating expected returns, particularly for portfolios concentrated in value and small-cap stocks.

Later, Fama and French (1993) expanded the CAPM by introducing two additional risk factors: size and value. In their earlier study, Fama and French (1992) initially demonstrated the multidimensional nature of stock risks, positing that size and the B/M ratio serve as proxies for systematic risks in the equity market. Small-cap firms consistently outperform large-cap ones, and high-value firms consistently outperform low-value ones. Building on this study, Fama and French (1993) developed the size factor by subtracting the average returns of small firms from those of large firms, and the value factor by subtracting the average returns of high B/M firms from those of low B/M firms. The size factor captures the risk of systematic outperformance of small companies over larger ones, while the value factor captures the risk of systematic outperformance of high B/M stocks over low B/M stocks. The Fama–French three-factor model (FF3FM) enhanced the explanatory power of the CAPM by 70–90%, generating alphas that are closer to zero.

Subsequently, Carhart (1997) expanded upon the framework established by Fama and French (1993) by introducing the momentum factor into the model, which was later recognised as the Fama–French–Carhart four-factor model (FFC4FM). Carhart argued that the significant persistent outperformance of mutual funds observed in earlier studies is not a result of managers adhering to momentum investment strategies, but rather, occurs by chance, as they hold relatively large positions in the preceding year's winning stocks. This four-factor model incorporates the momentum anomaly highlighted by Jegadeesh and Titman (1993). By capturing the momentum anomaly of persistence in returns for firms with high returns and with lower returns in the previous year, the FFC4FM gained prominence for several years in the literature on asset pricing models.

Then, Fama and French (2015) identified additional patterns in the returns of stock portfolios related to profitability and investment that could not be explained by the FF3FM. Consequently, they extended the FF3FM by adding two more factors to account for the risk associated with profitability and investment. The resulting five-factor model (FF5FM) significantly enhanced the FF3FM, increasing its explanatory power to 94%, reducing unexplained returns closer to zero and addressing the FF3FM's limitation in capturing the high average returns associated with share repurchases (Fama & French, 2015, 2016). The performance of the FF5FM has been notably superior to that of the FF3FM in international markets. Fama and French (2017) constructed portfolios for four pooled markets using the FF5FM: North America, Europe, Asia Pacific and Japan. While investment factors were redundant in Europe and Japan, asset pricing tests confirmed that the FF5FM captured the pattern in average returns better than the FF3FM. Foye (2018) conducted a comprehensive test of the FF5FM in emerging markets, revealing its outperformance over the FF3FM in five markets in Eastern Europe and five markets in Latin America. However, Asian markets did not yield significant premiums for profitability or investment. Last, Fama and French (2018) incorporated Carhart's (1997) momentum factor into the FF5FM and referred to it as the Fama–French–Carhart six-factor model (FFC6FM, hereafter). The FFC6FM reduced unexplained returns even closer to zero.

Multi-factor pricing models are commonly used to measure the performance of managed portfolios, such as mutual funds. While the FF5FM and FFC6FM have been shown to provide superior estimates of expected returns for hypothetical portfolios in developed and some emerging equity markets, there is a lack of evidence in the literature on their efficiency in explaining mutual fund returns. Therefore, this study aims to rank CAPMs by their efficiency in explaining mutual fund returns and proposes the following hypotheses to accomplish this goal:

Hypothesis 1 (1.A): Multi-factor models explain the returns of active funds better than the SFM.

Hypothesis 1 (1.B): The FF5FM explains the returns of active mutual funds better than the FF3FM.

Hypothesis 1 (1.C): FFC6FM explains the returns of active mutual funds more accurately than the FFC4FM.

The next subsection reviews the development of market timing models that differentiate between risk-adjusted fund returns attributable to market timing skills versus those attributable to stock-picking skills.

3.3.2 Market Timing Models

This section reviews the models that evaluate mutual fund managers' ability to outperform the market through market timing skills. The performance estimated by unconditional models, such as the FFC6FM, may stem from either the stock-picking skills (micro-forecasting skills) or market timing skills (macro-forecasting skills). The stock-picking skill involves acquiring undervalued stocks and shorting overvalued stocks, while the market timing skill entails investing in aggressive assets during an upward market and defensive assets during a downward market. Jensen (1972) demonstrated the impossibility of applying SFM specifications (similarly applicable to the multi-factor models in Equations 5 to 8) to separate the incremental performance attributable to stock-picking skills from that attributable to market timing skills. Specialised models have been developed to address this issue, with the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model being key contributions to the market timing literature.

First, the Treynor and Mazuy (1966) model, built upon the CAPM, aims to assess the ability of mutual fund managers to time significant market fluctuations and generate corresponding risk-adjusted returns. The model posits that given the expectation for fund managers to maintain well-diversified portfolios, these portfolios will exhibit relatively constant volatility over time. Consequently, the scatter of portfolio returns will closely follow the market line, producing returns around the market owing to effective diversification. However, Treynor and Mazuy (1966) argued that having a well-diversified portfolio is not the sole objective for most fund managers; rather, they are keen on outguessing the market. The model assumes that fund managers adjust their portfolio holdings to include low-volatility assets (reducing the portfolio's beta to less than 1) when anticipating a bearish market, and high-volatility assets (increasing the portfolio's beta to more than 1) when anticipating a bullish market. If fund managers accurately predict the market direction most of the time, the linear characteristic line of CAPM may become invalid, and a quadratic characteristic line (a convex function) would better predict mutual fund returns. Treynor and Mazuy (1966) introduced a quadratic variable of market returns to the CAPM to account for managers' market timing skills, whereby a positive and significant coefficient for the quadratic variable indicates the presence of market timing skills.

Next, in their market timing model, Henriksson and Merton (1981) built upon the CAPM and the Merton (1981) theoretical framework. They proposed that mutual fund managers make forecasts about either a bullish or bearish market. In the event of anticipating a bear market, managers would adopt a protective put option investment strategy equivalent to their investment in the equity market. The model assumes that mutual fund managers would exercise their options in a bear market, resulting in equal returns. Henriksson and Merton (1981) introduced a market timing forecast coefficient to account for potential excess returns in bear markets. The probability of correctly forecasting the market is conditional upon the realised return on the market. A positive and significant market timing coefficient suggests that fund managers possess the ability to accurately time the market, while a negative or non-significant market timing coefficient indicates their lack of market timing skills.

Other models have also been employed to assess potential market timing skills. Ferson and Schadt (1996) modified a conditional market timing model by integrating public information into portfolio holdings, including factors such as a lag of the one-month T-bill yield, of the market's dividend yield, of the term structure's slope and of the quality spread in the corporate bond market, and a dummy variable for the January effect. Others have also attempted to developed different models. For example, Pesaran and Timmermann (2002) provided a generalisation of the Henriksson and Merton (1981) non-parametric test of market timing, Ferson and Khang (2002) suggested a conditional model using portfolio weights, W. Jiang (2003) proposed a non-parametric test that is structured to proxy the probability that a manager loads on more market risk when the market return is relatively high and G. Jiang et al. (2007) developed and implemented new measures of market timing based on mutual fund holdings.

In conclusion, the two specific models of focus in this study are the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model. This study will apply these models in their original forms and will incorporate them into the FFC6FM framework, which will be explained further in Chapter 4. The subsequent subsection reviews the implications of market proxies on the accurate measurement of mutual fund performance.

3.3.3 Market Proxy and Mutual Fund Performance

The selection of appropriate market return proxies is crucial to ensuring the accurate measurement of mutual fund performance, regardless of the applied models. The choice of a benchmark index in asset pricing or market timing models that fails to adequately represent the constituents of mutual funds in terms of returns and risks can lead to misleading results (Fama & French, 2004; Grinblatt & Titman, 1989, 1994; Lehmann & Modest, 1987; Mateus et al., 2019; Roll, 1977, 1978).

The first challenge is defining the market portfolio. There is theoretical ambiguity regarding assets that should be excluded from the portfolio, and data availability significantly limits the assets that can be included (Fama & French, 2004). Grinblatt and Titman (1994) applied different performance measures using various market proxies. They found that, generally, different measures led to similar conclusions about performance when using the same benchmark. However, variations in such conclusions arose when employing different benchmarks even for similar measures, emphasising the substantial impact of selecting the market portfolio on mutual fund performance inferences. Moreover, Lehmann and Modest (1987) contributed to this understanding by constructing benchmark indices based on 10 common factors, including 250 and 750 stocks. Their study revealed significant differences between the performance measured using standard SFM benchmarks and that using arbitrage pricing theory benchmarks. This underscores the importance of selecting an appropriate model for risk and expected return. Coles et al. (2006) examined how benchmark misspecification could bias performance inference by using two standard indices: the S&P 500 index and the Center for Research in Security Prices, LLC (CRSP) value-weighted index with a sample of 327 equity-oriented mutual funds. They found empirical evidence that market benchmark misspecifications cause severely biased overall performance inference.

Most studies on the Saudi Arabian market have used TASI to evaluate mutual fund performance for it serves as a standard benchmark index. However, TASI might not be appropriate for some mutual funds, specifically those that accumulate dividends. Throughout the analysis of mutual fund performance in this thesis, three different benchmark indices have been applied. First, TASI serves as the standard benchmark of the Saudi market based on the price level. TASI includes all stocks in the market on the value-weighted basis. Second, the MSCI-SADI serves as an active benchmark index. Unlike TASI, MSCI-SADI is reconstructed quarterly by using six common factors: value, size, momentum, quality, yield and volatility. The index includes 35 to 40 stocks that represent about 85% of the Saudi equity market. This index is more suitable to generate passive returns that track the performance of active portfolios.

Third, S&P-SADITR serves as a total returns index. The advantage of this index is that it captures both price-level and dividend-level returns, which makes it suitable for measuring the performance of mutual funds that do not distribute dividends. Measuring the performance of funds with several market indices can provide clearer insight, as inferences can vary when using different benchmarks (Grinblatt & Titman, 1994). Therefore, in the next section that outlines hypotheses on mutual fund performance, this study adds Hypotheses 2.C, 2.F, 2.J, and 2.M to compare performance results adjusted by different benchmark indices. This deliberate inclusion aims to systematically assess and analyse the impact of benchmark choices on the outcomes of the performance assessment.

3.4 Mutual Fund Performance

This section reviews empirical literature on mutual fund performance. It will cover three main types of performance analysis: benchmark-adjusted return performance on active and passive funds, risk-adjusted return performance on active and passive funds, and market timing ability on active funds. Then, it identifies potential gaps in the literature and develops hypotheses.

3.4.1 Benchmark-Adjusted Return Performance

This subsection explores the findings of prior studies that employ the benchmark-adjusted performance (mean difference) measure, a straightforward approach commonly employed to evaluate mutual fund performance. This measure assesses whether mutual funds achieve significantly higher returns than the benchmark indices. The calculation involves determining the difference between the unadjusted returns of mutual funds and those of benchmark indices, followed by a *t*-test to evaluate the statistical significance of this difference from zero. Significantly, this method does not make adjustments for mutual fund returns based on other systematic risk factors associated with the fund's investment style, such as size, value and momentum.

Several studies have employed this approach to evaluate the performance of active funds in both developed and emerging markets (Banegas et al., 2013; Barber et al., 2016; J. Chen et al., 2004; Garyn-Tal, 2015; Mansor et al., 2015). For instance, Banegas et al. (2013) analysed a sample of 4,200 European funds across the 1988–2008 period as well as the subsample periods of 1988–1998 and 1999–2008. Their results indicated that over the full period and over the 1988–1998 subsample period, the funds' unadjusted returns significantly underperformed the benchmark index by 1.18% and 2.48%, respectively. However, during the 1999–2008 period, these funds' unadjusted returns significantly outperformed the benchmark index returns by 0.34%. Similarly, Mansor et al. (2015) assessed the benchmark-adjusted performance of 106 Malaysian active funds in 1999–2009. Their empirical results revealed that the unadjusted returns of Islamic, non-Islamic and the entire sample of mutual funds were significantly higher than those of the market index.

As regards the Saudi market, some studies have concluded that there is no evidence of superior fund performance when benchmark-adjusted performance is used. For instance, BinMahfouz and Hassan (2012) analysed the performance in 2005–2010 of 26 Islamic funds and 20 conventional funds against MSCI-SADI and MSCI-SADI-Islamic. Similarly, Omri et al. (2019) examined the performance of 12 Islamic funds and seven conventional ones in 2009–2014 against the Dow Jones Islamic GCC Index and Dow Jones GCC Index. In addition, Zouaoui (2019) measured the benchmark-adjusted performance of 15 mutual funds managed by HSBC between 2011 and 2018. All three studies found no evidence of a significant difference in mean returns between funds and their benchmark indices. In contrast to these studies, Al Rahahleh and Bhatti (2022) examined the benchmark-adjusted performance in 2007–2016 of 25 shariah-compliant funds, 14 conventional funds and all these 39 funds, against TASI. They found that only the conventional funds generated a significant unadjusted return of 0.418 higher than the TASI unadjusted returns. Moreover, the sample that included all 39 funds had unadjusted returns higher than TASI by 0.41, which was attributed to the performance of the conventional funds.

However, given the limitations of small sample sizes and short study periods in prior studies, further investigation is needed to thoroughly understand mutual fund benchmark-adjusted performance in the Saudi Arabian market. Moreover, to gain a more accurate understanding of the performance of active funds in Saudi Arabia, it is crucial to consider benchmark-adjusted performance alongside other measures, especially considering the inconsistent results of earlier studies. Therefore, the following hypothesis is proposed:

Hypothesis 2 (2.A): The unadjusted return of active mutual funds differs significantly from the unadjusted market return.

Hypothesis 2 (2.B): The benchmark-adjusted return performance of active funds during SMEs varies from that during the overall sample period.

Hypothesis 2 (2.C): The inference about the benchmark-adjusted return performance of active funds varies when using different market return proxies.

Although passive mutual funds aim to track the returns of their benchmark indices, their performance may differ. The monthly return performance of funds may lag or surpass that of their benchmark indices because of various factors, such as management fees, cash holding, dividends, inflows and outflows and replication strategies (Charupat & Miu, 2013), necessitating performance analysis. However, only a limited number of studies have applied benchmark-adjusted analysis to examine the performance of passive mutual funds in developed markets.

In general, passive funds in developed markets are less likely to outperform or underperform their benchmark indices. Harper et al. (2006) analysed passive fund performance in various countries,[13] finding that except in Malaysia, passive funds generated slightly negative performance compared with their benchmark indices. However, the performance of none of the funds differed significantly from zero. Elton et al. (2019b) examined both index funds and ETFs investing in the US and emerging markets. They found that regardless of whether funds were categorised by type (index funds v. ETFs) or geographical investment (US market v. emerging markets), the average difference in returns between passive funds and their benchmark indices was non-significant. In contrast, Blitz et al. (2012), who measured the performance of 40 European

[13] The countries were Australia, Austria, Hong Kong, France, Germany, Italy, Japan, Malaysia, Mexico, Singapore, Spain, Switzerland, the United Kingdom and the US.

passive funds in 2003–2008, found that these funds significantly underperformed their benchmark indices by 0.5% to 1.5% per year. They attributed this underperformance to expense ratios.

To enhance the understanding of passive fund performance in Saudi Arabia and to compare it with active fund performance, it is necessary to consider benchmark-adjusted performance. As far as we know, no study has applied a benchmark-adjusted analysis to measure passive fund performance in the Saudi Arabian market. Accordingly, the following hypothesis is proposed:

Hypothesis 2 (2.D): The unadjusted return of passive mutual funds differs significantly from the unadjusted market return.

Hypothesis 2 (2.E): The benchmark-adjusted return performance of passive funds during SMEs varies from that during the overall sample period.

Hypothesis 2 (2.F): The inference of the benchmark-adjusted return performance of passive funds varies when using different market return proxies.

This study compares the benchmark-adjusted performance of active funds to that of passive funds. Once such performance of both types of funds has been assessed against their respective benchmark indices, it is important to compare their performance directly, particularly given the evidence that market benchmark indices are 'paper portfolios' that are not investable and thus do not incur costs (Frino & Gallagher, 2001). As discussed earlier, the literature has used the benchmark-adjusted measure approach to compare Islamic mutual fund performance to conventional mutual fund performance in the Saudi market (Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Omri et al., 2019; Zouaoui, 2019). Further, some studies on other countries have used it to compare ethical versus conventional mutual fund performance (Bauer et al., 2005, 2007). To address a part of its second objective, this study uses this approach to examine whether the unadjusted return of active funds significantly differs from that of passive funds over the overall sample period and during SMEs by proposing the following hypothesis. Notably, this study is likely the first to adopt this approach in the Saudi context.

Hypothesis 2 (2.G): The benchmark-adjusted performance of active funds differs significantly from that of passive funds during the overall sample period and SMEs.

3.4.2 Risk-Adjusted Return Performance

This subsection reviews empirical studies that have applied CAPMs to estimate the risk-adjusted return performance of active and passive funds. Several influential academic studies have been conducted on the performance of both types of funds in developed and emerging markets. In this section, first, the early seminal works in this field, and then, the most recent studies, are reviewed.

Researchers have long focused on the performance of active mutual funds in developed markets. For instance, Jensen (1968), in a pioneering study, used the SFM to measure the performance of 115 active funds in the US during 1955–1964. This study suggested that active funds do not provide additional value to investors because mutual funds underperform the market both before and after the inclusion of management fees. Subsequent empirical studies yielded different conclusions. In contrast, Ippolito (1989), who evaluated the performance of 143 US mutual funds in 1965–1984 using Jensen's alpha, reported significantly positive risk-adjusted performance for funds with higher load charges. Further, Grinblatt and Titman (1989), who were among the first to employ Jensen's alpha to measure mutual fund performance, found that mutual funds outperformed passive indices between 1975 and 1984. Using a different methodology, Grinblatt and Titman (1993) employed quarterly portfolio holdings to assess the performance of 155 mutual funds in 1974–1984, and similarly, found that mutual funds outperformed passive indices. In addition, Elton et al. (1993) compared two influential studies—those of Jensen (1968) and Ippolito (1989). Significantly, Elton et al. suggested that the significant positive risk-adjusted returns in Ippolito's study could be attributed to the effect of non-S&P 500 assets. They re-measured the performance of a similar sample with an adjusted benchmark index and did not find any significant risk-adjusted returns.

Later, studies on the impact of survivorship bias introduced conflicting results into the debate over mutual fund performance in developed markets. Malkiel (1995) employed Jensen's alpha to analyse US mutual fund performance in 1971–1991. This analysis revealed that surviving funds outperformed liquidated funds by 150 basis points, highlighting the effect of survivorship bias on the conclusions drawn in prior studies that did not account for the performance of liquidated mutual funds. Malkiel's results imply that even surviving funds fail to produce risk-adjusted return performance for investors after expenses. These findings were reaffirmed with an updated sample for 1970–2017 (Malkiel, 2020, pp. 156–163).

Furthermore, Carhart (1997) developed the FFC4FM to measure a sample of mutual funds free of survivorship bias and showed that the results did not support the superiority of active funds, even before management fees. In addition, Wermers (2000) conducted a comprehensive analysis of mutual fund holdings in 1974–1994 and found that mutual fund holdings outperformed the market by 130 basis points. However, this performance disappeared after accounting for management expenses and transaction costs.

Recent studies on mutual fund performance in developed markets present conflicting results. For example, Ferreira et al. (2013) assessed the performance of 37,910 mutual funds across the US and 25 other countries. Using the FFC4FM, they found that mutual funds in the US and 12 other countries underperformed compared with market returns, whereas mutual funds outperformed in the remaining 13 countries. However, the overall sample demonstrated mutual fund underperformance in comparison to market returns. In contrast, Avramov and Wermers (2006) found that the incorporation of the predictability of manager skills is the primary driver of investment profitability. Strategies incorporating this predictability, such as long-only strategies, outperformed benchmarks by 2 to 4% annually through skilful industry timing over the business cycle. Moreover, by selecting funds that outperform their industry benchmarks, investors can gain an additional 3 to 6% annually. Furthermore, Otten and Bams (2002) examined the performance of mutual funds in France, Germany, Italy, the Netherlands and the United Kingdom. Analysing a sample of 506 equity funds for 1991–1998, they used the FFC4FM and found that mutual funds, especially small-cap funds, exhibited superior performance in France, Italy, the Netherlands and the United Kingdom, even after considering returns after costs. Overall, mutual fund performance in developed economies remains a subject of debate because of disputes over sample periods, survivorship bias, appropriate benchmark indices, performance measurement models and other methodological approaches.

Similarly, mutual fund performance in emerging markets presents a varied landscape, with studies reporting contrasting results. For instance, Kiymaz (2015) and Rao et al. (2017) evaluated a total of 581 and 817 mutual funds in China, respectively, over different time frames. Both studies found that mutual fund managers in China were able to generate positive and significant alpha. Kiymaz (2015) further categorised the funds, noting that aggressive allocation funds offered the highest alpha, followed by moderate allocation funds, while conservative allocation funds exhibited the least alpha. In contrast, Białkowski and Otten (2011) analysed the performance of 140 Polish mutual funds in 2000–2008. Using the FFC4FM, they found that most had negative alphas, indicating underperformance against their benchmark indices. However, they attributed this underperformance to high management expense ratios, as mutual funds had significant and positive alphas on measuring their performance using gross returns. Hili et al. (2016) focused on managers investing in emerging market funds and found that they did not outperform the market as a whole. These managers tended to be cautious in constructing portfolios, favouring investments in large-cap equity funds to minimise exposure to risks related to liquidity, stability and volatility. Huij and Post (2011), who compared the performance of active funds in emerging markets with those in the US, provided an interesting perspective—they discovered that, unlike US funds, emerging market funds outperformed their benchmark indices, and this outperformance persisted over time.

As regards Saudi Arabia, its active mutual funds operate within a unique capital market that differs from developed as well as emerging markets. Notably, there is substantial evidence indicating weak-form inefficiency in stock prices within this context (Al-Ajmi & Kim, 2012; Budd, 2012; Butler & Malaikah, 1992; Syed & Bajwa, 2018). The market exhibits high volatility, which is primarily attributed to a robust correlation with the oil market (Almohaimeed & Harrathi, 2013; Arouri et al., 2011; Arouri & Rault, 2010, 2012; Hammoudeh & Aleisa, 2004; Zarour, 2006). In addition, there are a large number of individual traders, often characterised as noise traders, and substantial government ownership in the market (Tadawul, 2020). These distinctive operational features of this capital market underscore the necessity for a targeted examination of the Saudi Arabian mutual fund industry.

However, a limited number of studies have specifically focused on the risk-adjusted return performance of equity mutual funds in Saudi Arabia. Mutual fund performance in Saudi Arabia has received inadequate research attention in terms of the industry's capitalisation and its fast growth. In addition, several studies have methodological issues. For instance, Merdad et al. (2010) used the SFM to examine the risk-adjusted performance of 12 Islamic funds and 16 conventional funds managed by HSBC in 2003–2010. They found that the single-factor alpha was not statistically significant for both Islamic and conventional funds when regressed against the GCC Islamic Index, MSCI World Islamic Index, TASI and MSCI World Index.

However, this study is marred by significant methodological issues, as highlighted by BinMahfouz and Hassan (2012). First, Merdad et al. (2010) grouped mutual funds with inconsistent asset class types (money market, fixed income and equity) and inconsistent geographical focus (globally invested and locally invested) into two portfolios: Islamic and conventional. Second, they employed global and local equity market indices to benchmark portfolios that comprised different asset classes and invested in different geographical markets. This approach yields misleading results, as evidenced by the notably low *R*-squared values in the regression analysis. To address these methodological challenges, Merdad et al. (2016) expanded their sample of locally focused funds to 52 Islamic and 30 conventional funds. Employing the SFM and the FFC4FM, they assessed risk-adjusted performance against TASI and the GCC Islamic index. The SFM results indicated that Islamic and conventional funds both did not outperform the market. Conversely, the FFC4FM suggested that only Islamic funds demonstrated an ability to outperform the market, as represented by TASI.

Further, both BinMahfouz and Hassan (2012) and El-Mousallamy and El-Masry (2016) arrived at similar conclusions. BinMahfouz and Hassan (2012) employed the SFM and the FF3FM to assess the risk-adjusted performance of 26 Islamic funds and 20 conventional funds during 2005–2010 against MSCI-SADI and MSCI-SADI-Islamic. The empirical findings revealed a lack of evidence supporting superior performance. Regardless of the pricing model used, the estimated risk-adjusted performance for both Islamic and conventional funds proved to be non-significant. Similarly, El-Mousallamy and El-Masry (2016) utilised both the SFM and the FF3FM to compare the risk-adjusted returns during 2005–2011 of 10 Islamic funds and 11 conventional funds, against TASI. In concordance with BinMahfouz and Hassan (2012), the results indicated a lack of superior performance. The estimated single-factor alphas and three-factor alphas for both Islamic and conventional mutual funds were statistically non-significant.

Indeed, the studies by Al Rahahleh and Bhatti (2022) and Ashraf (2013) present a notable contrast with the aforementioned studies, for they acknowledge the positive and significant outperformance of the mutual funds in their overall sample. Al Rahahleh and Bhatti (2022) employed the FFC4FM to assess the performance in 2007–2016 of 25 shariah-compliant and 14 conventional funds, as well as the sample of all 39 funds, against TASI. Their analysis showed that conventional funds exhibited a positive and significant outperformance of the benchmark index by 0.303% on a monthly basis, whereas Islamic funds displayed a negative and non-significant alpha. However, the full sample of 39 funds demonstrated a positive and significant outperformance of the benchmark index by 0.256% on a monthly basis, predominantly driven by the outperformance of conventional funds. In contrast, Ashraf (2013) employed the SFM to compare the performance of 49 shariah-compliant and 59 conventional funds against TASI between 2007 and 2011. This comparison revealed that Islamic funds positively and significantly outperformed the benchmark index by 0.138%, while conventional funds produced a non-significant alpha. Despite both studies arriving at a consensus that all mutual funds outperformed the market, there was a stark contradiction in the performance of fund types based on characteristics, as Al Rahahleh and Bhatti (2022) found significant outperformance only for conventional funds and Ashraf (2013) found the opposite.

In addition, Omri et al. (2019) assessed the risk-adjusted performance of 12 Islamic funds and seven conventional funds, employing both the SFM and FFC4FM. Spanning from 2009 to

2014, the study benchmarked both Islamic and conventional funds against the Dow Jones Islamic GCC Index and the Dow Jones GCC Index. The SFM results indicated that both fund types exhibited significant and positive alphas when benchmarked against the Dow Jones GCC Index. In addition, only Islamic funds demonstrated significant and positive alphas on benchmarking both fund types against the Islamic index. The FFC4FM results showed that Islamic funds exhibited an annual outperformance of 6.95% against the Islamic index, whereas neither fund type could outperform the conventional index. A notable methodological concern in this study is the adjustment of Saudi mutual fund returns to the GCC index, which could lead to misleading conclusions.

The present literature review highlights a significant inconsistency in the conclusions drawn regarding the performance of active mutual funds, suggesting potential methodological issues. One primary concern is the possibly inappropriate use of benchmark indices as market proxies.[14] In an effort to address this issue, the present study employs three distinct methodologies for calculating Saudi market returns, aiming to derive more reliable and consistent conclusions. A second methodological concern involves the application of incomplete asset pricing models, which may fail to adequately adjust for the potential risks undertaken by mutual funds, leading to potential inaccuracies in performance assessments. This study aims to identify the most efficient model in the asset pricing literature for measuring mutual fund performance. Subsequently, the chosen model will be applied to estimate risk-adjusted returns, providing a more comprehensive understanding of mutual fund performance.[15] The third potential issue is the lack of control for survivorship bias in most past studies on mutual fund performance in Saudi Arabia, despite well-documented evidence of its impact (Malkiel, 1995). To mitigate this concern, this study includes

[14] This issue was discussed in detail in Subsection 3.3.3.
[15] This issue was discussed in detail in Subsection 3.3.1.

both existing and liquidated funds in the analysis, and thus provides a more accurate representation and controls for survivorship bias.

By addressing these methodological issues, the modified methodologies employed in this study aim to enhance the precision of risk-adjusted return performance measurement and deliver robust results. The study proposes the following hypothesis to further investigate and contribute to the understanding of mutual fund performance in the Saudi Arabian context.

Hypothesis 2 (2.H): Active funds generate positive and significant risk-adjusted return performance (alpha) during the overall sample period and SMEs.

Hypothesis 2 (2.I): The risk-adjusted performance (alpha) of active funds during SMEs varies from that during the overall sample period.

Hypothesis 2 (2.J): The inference of active fund risk-adjusted performance (alpha) varies when using different market return proxies.

Despite the widespread prevalence of passive investing in developed markets, the literature has tended to overlook the performance of passive funds and has often focused instead on aspects such as tracking accuracy and pricing efficiency. Only a handful of studies have utilised the SFM to assess the risk-adjusted performance of passive funds. One such study is that by Shin and Soydemir (2010), who investigated the risk-adjusted performance of 26 passive funds across Asia, Europe, America and the US during 2004–2007. They revealed that the Jensen's alpha coefficients were consistently significant and negative, with the exception of two funds that exhibited significant and positive alphas. The prevalence of statistically significant and negative alpha values suggests the inability of passive fund managers to outperform benchmark indices, primarily because of the burden of high expenses.

Further, Khan et al. (2015) compared the performance of 27 passive funds from developed markets with that of 18 funds from emerging markets in 2007–2014. Their empirical results indicated that the risk-adjusted performance of passive funds in emerging markets tended to be slightly higher than that of their counterparts in developed markets. However, all measured alphas were statistically non-significant, confirming the nature of passive funds to closely track the returns of their benchmark indices. In addition, Milonas and Rompotis (2006) focused on 36 passive funds in Switzerland. While the alphas in this study tended to be negative, the close alignment of these funds with benchmark indices meant that most alphas were statistically non-significant.

Similarly, the performance of passive investment funds in Saudi Arabia has received minimal research attention, and only Diaw (2019) has conducted a study in this context. Diaw found significant and negative alpha values for all the funds, pointing towards a considerable underperformance of passive funds. However, it is crucial to note that the low *R*-squared values in the regressions may suggest a potentially inappropriate choice of benchmark index. Thus, in view of the limitations of this prior study, there is a compelling need for a more comprehensive analysis of passive fund performance in Saudi Arabia. Such an analysis requires expanding the sample size and carefully selecting three accurate benchmark indices to enhance the robustness of the study. In response to this gap in the literature, the current study presents the following hypotheses:

Hypothesis 2 (2.K): Passive funds generate positive and significant risk-adjusted return performance (alpha) during the overall sample period and SMEs.

Hypothesis 2 (2.L): The risk-adjusted performance (alpha) of passive funds during SMEs varies from that during the overall sample period.

Hypothesis 2 (2.M): The inference of the risk-adjusted performance (alpha) of passive funds varies when using different market return proxies.

Recent studies have primarily focused on comparing the performance of active funds with that of passive funds. However, market benchmark indices represent returns of paper portfolios, which are not investable and do not incur any costs (Frino & Gallagher, 2001). Therefore, for a more realistic and feasible comparison, direct comparisons of active and passive funds are deemed more appropriate.

Several studies have presented evidence of comparable performance between active and passive management. For example, Pace et al. (2016) conducted a comprehensive comparison of risk-adjusted return performance between active and passive funds in the US and Europe, from January 2004 to December 2014. They divided 776 funds into 12 equally weighted active and passive portfolios and applied the SFM, the FF3FM and the FFC4FM to estimate risk-adjusted return performance. Their results indicated positive and significant performance for active management when calculated by gross returns. However, on considering net returns, they found that neither active nor passive management was superior in terms of risk-adjusted performance, with most estimated alphas being non-significant. Another study by Crane and Crotty (2018) conducted a comparison to a sample of 2,060 funds for the 1995–2013 period. They showed that passive fund risk-adjusted performance exists and persists in a similar proportion to that of active funds. Similarly, Shreekant et al. (2020) provided additional evidence from the Indian market, suggesting there was no significant difference in the performance of active and passive funds.

Contrary to these findings, some studies have suggested that passive funds may outperform active funds. Elton et al. (2019a) formed portfolios of passive funds matching the risk of 883 active funds and found that approximately 78% of these portfolios had higher returns than did the active funds. Moreover, on average, the difference in returns between these portfolios and the active fund was 1.37% per year. Further, Harper et al. (2006) proposed that passive funds, represented by ETFs, exhibit higher mean returns and higher Sharpe ratios than active funds represented by closed-end funds. However, their findings may be influenced by a notable bias due to the methodology they employed, for they used the market prices of closed-end funds to represent active funds and those of ETFs to represent passive funds for the comparison. In fact, ETF market prices are widely recognised for their precision in tracking their net asset value (NAV; Buetow & Henderson, 2012), whereas closed-end funds are known to be traded at significant discounts to their NAV (C. Lee et al., 1990), resulting in lower returns than the actual returns reported by NAV.

Despite these insights from these comparisons in developed markets, there is a critical gap in the analysis of portfolio management within the Saudi Arabian context. To date, no study has directly compared the performance of active and passive funds in Saudi Arabia. This study aims to fill this gap by developing the following hypothesis, contributing evidence to the finance literature on Saudi Arabia:

Hypothesis 2 (2.N): The risk-adjusted performance (alpha) of active funds significantly differs from that of passive funds.

3.4.3 Market Timing Ability

The literature on mutual funds has placed significant emphasis on evaluating fund managers' market timing abilities, a crucial aspect in portfolio management that assesses their capacity to predict major market fluctuations.

In their pioneering study, Treynor and Mazuy (1966) applied the market timing model they developed to 57 mutual funds in the US market for the 1983–1995 period. Surprisingly, among the results for the managers of these 57 funds, those for only one manager exhibited a significant curved line, which meant that the overall empirical results did not provide significant evidence supporting the market timing ability of mutual fund managers. Later, Kon and Jen (1979), who used the SFM framework, applied the switching regression technique to a sample of 49 US mutual funds. Their empirical results indicated that a considerable number of mutual funds significantly changed their risk levels during the measured interval, resulting in superior performance. This finding implies a dynamic adjustment in response to market conditions, suggesting potential market timing abilities among certain fund managers.

Moreover, Ferson and Schadt (1996) contributed to this body of literature by employing conditional models based on the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model. Ferson and Schadt focused on 67 US mutual funds for the 1968–1990 period. They noted that the application of conditional versions enhanced the efficacy of these models. Notably, the funds exhibited spurious inferior performance, which they primarily attributed to a negative covariance between mutual fund betas and the conditional expected market return.

Furthermore, some studies have investigated the market timing skills of mutual fund managers, with a particular focus on emerging capital markets. Yi et al. (2018) examined the performance of 336 Chinese mutual funds in 2005–2016 by applying the Treynor–Mazuy and Henriksson–Merton models. Their empirical results revealed that 20.8% and 22.9% of these funds exhibited significant market timing ability based on the Treynor–Mazuy and Henriksson–Merton models, respectively. In contrast, Dhar and Mandal (2014), who focused on managers of 80 Indian mutual funds in 2000–2012, found that most fund managers were unable to correctly time the market using the same models.

Turning to the Saudi Arabian context, a few studies have explored the market timing skills of mutual fund managers, often with a focus on limited number of funds for a specific fund provider. Zouaoui (2019), who applied a conditional model based on the Treynor and Mazuy (1966) model to analyse 15 Saudi mutual funds managed by HSBC in 2011–2018, concluded that local mutual funds, both Islamic and conventional, lacked significant market timing skills. Similarly, Merdad et al. (2016) applied the Treynor and Mazuy (1966) model on a locally focused sample of 52 Islamic funds and 30 conventional funds. Their empirical results revealed negative and significant market timing coefficients for Islamic funds during various market conditions.

Recognising the limitations of previous studies, the current research seeks to address these issues by conducting a comprehensive analysis of mutual fund managers' market timing ability in Saudi Arabia. First, it extends the sample to cover all available locally focused mutual funds over an extensive period of 11 years that encompasses SMEs. Second, it measures fund returns against three different benchmark indices. Most importantly, the study employs two key market timing models—the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model—in their original forms and also integrates these into the FFC6FM framework. With these improvements, the study puts forth the following hypothesis to contribute to the understanding of mutual fund market timing in the Saudi Arabian context:

Hypothesis 2 (2.O): Active mutual funds possess significant market timing skills during the overall sample period and SMEs.

3.5 Mutual Fund Performance During Significant Market Events

SMEs refer to extraordinary occurrences, such as periods of extreme declines or fundamental regulatory changes that exert a temporary or permanent effect on capital markets. These events may trigger distinct behaviours in mutual fund performance, thereby influencing their value proposition to investors. Moskowitz (2000) argued that mutual funds may exhibit unique behaviour in special periods, specifically in market downturns. The current study is specifically oriented towards assessing mutual fund performance across various market conditions, including bearish and bullish periods, as well as during two recent financial crises in the Saudi capital market. It also examines mutual fund performance before and after the significant financial reforms implemented in the Saudi capital market in 2015.

3.5.1 Mutual Fund Performance During Financial Crises

Mutual fund performance has exhibited distinctive behaviour during SMEs. Drawing on empirical evidence from developed capital markets, Kosowski (2011) compared mutual fund performance during recession and expansion periods from 1962 to 2005. The findings revealed statistically and economically significant risk-adjusted performance (alpha) of 3–5% per year during recessions, surpassing performance during expansion periods. Similarly, Petajisto (2013) analysed mutual fund performance during January 1990 – December 2009 and identified extraordinary risk-adjusted returns of 1.12% to 9.41% during the second year of the financial crisis in 2008–2009.

In the Saudi equity market context, Merdad et al. (2010) observed that shariah-compliant funds underperformed benchmark indices during overall and bullish periods. However, they significantly outperformed their benchmarks during bearish periods and the 2008–2009 financial crisis. In addition, Al Rahahleh and Bhatti (2022) divided their full-sample study period (April 2007 – October 2016) into three subsample periods based on volatility. They found that all mutual funds, both Islamic and conventional, significantly and positively outperformed the market by 0.329% during low-volatility periods, but they did not observe significant performance during high- and medium-volatility periods.

In the recent past, the Saudi capital market experienced two financial crises—one in 2014–2016 and the other in 2019–2020. The first crisis resulted from intense oil price competition among major oil-producing countries during 2014–2016, coupled with severe cuts in government spending, causing a 49% decline in the Saudi equity market.[16] To illustrate, Plot A of Figure 2.2 shows that the market index declined from 10,900 points in September 2014 to about 5,600 points in September 2016. The second crisis, sparked by oil price competition and exacerbated by the COVID-19 pandemic in 2020, led to extreme declines in the Saudi Arabian GDP and equity market. This is illustrated in Plot A of Figure 2.2—the market decreased from 9,300 to 6,500, which is a loss of more than 30% of its market capitalisation. This study aims to investigate how mutual funds performed during these financial crises of 2014–2016 and 2019–2020. Given the unique behaviour demonstrated by mutual funds during past crises and the absence of research on the performance of Saudi Arabian mutual funds during these recent financial crises, the study seeks to contribute valuable insights to the understanding of mutual fund behaviour in turbulent market conditions.

3.5.2 Financial Reforms of 2015 in the Saudi Capital Market

In June 2015, the SACMA initiated significant reforms, dismantling decades-old barriers to foreign investment in the Saudi equity market. These reforms included allowing QFIIs direct access to the local market, increasing the maximum ownership of foreign investors in publicly traded companies from 25% to 49% (Rashad, 2019) and elevating the Saudi market from a frontier market to an emerging market. Notably, the Saudi market was integrated into three major emerging market indices: MSCI, FTSE Russell and S&P (Tadawul, 2019).

These reforms aimed to attract a diverse array of new participants to the Saudi capital market. The integration with emerging market indices, such as MSCI (2.6%), FTSE Russell (3%) and S&P (2.57%),[17] obligated foreign funds, especially those focused on emerging markets, to

[16] The relationship between the Saudi equity market and oil market was explained in Chapter 2.
[17] Weights change according to fluctuations in market capitalisation.

include the Saudi market in their portfolios to align with these indices. Consequently, monthly ownership and trading activity reports revealed a surge in QFII participation, with ownership values skyrocketing from approximately USD0.02 billion in July 2015 to more than USD42 billion in December 2020. Moreover, the reports revealed that the volume percentage traded in the Saudi market by foreign investors increased from approximately 3% in December 2015 to 13.5% in December 2019 (Tadawul, 2020).

Empirical evidence in the literature has confirmed the hypothesis that the flows of foreign institutional investors into emerging markets bring about operational improvements. For example, foreign investors contribute to stabilising stock price volatility and minimising speculative trading (Han et al., 2015; Li et al., 2011; Vo, 2015). Moreover, their entry increases the efficiency and liquidity of emerging markets (Kacperczyk et al., 2018; J. Lee & Chung, 2018; Lin & Fu, 2017; Mitton, 2006). The financial reforms have already resulted in positive effects on the Saudi equity market. Foreign investors' participation has improved the overall market performance (Almutiri, 2020), and the liberalisation of the Saudi stock market has improved the stock price discovery process (valuation) and decreased bid–ask spreads (liquidity) and high–low price volatility (Sharif, 2019). These improvements may mitigate the influence of local individual traders on the market.

As aforementioned, the literature has provided empirical evidence about the distinctive performance of mutual funds during SMEs as against during normal periods. Considering this evidence and given that no study has focused on mutual fund performance during the two recent financial crises in 2014–2016 and 2019–2020 or before and after the 2015 financial reforms, this study fills this gap and examines Saudi Arabian mutual fund performance during these SMEs. The examination of these subsample periods will provide insights into the performance of the funds during these critical events and market transformations.

3.6 Persistence in Active Mutual Fund Performance

Sections 3.4 and 3.5 reviewed studies that evaluated aggregate mutual fund performance by measuring the average alpha of all mutual funds. However, when considering aggregate mutual fund performance, funds with significantly positive alphas might be balanced out by funds with significantly negative alphas. In this case, it is crucial to distinguish skill from luck. Therefore, the portfolio management literature has also focused on individual mutual fund performance persistence, seeking to understand whether funds with superior performance consistently outperform the market and whether those with inferior performance consistently underperform.

Distinguishing persistence in superior performance resulting from managerial skills can be challenging because luck may also play a role. In a vast pool of existing mutual funds, some may achieve superior performance purely by chance. To illustrate, envision 10,000 fund managers flipping a coin instead of making investment decisions, where heads represent superior performance and tails represent inferior performance. In such a scenario, a subset of managers may obtain consecutive heads or tails merely because of chance. Malkiel (2020) discussed the impact of luck on mutual fund performance persistence, providing detailed examples in this area of study.

Studies have developed various methodologies to examine mutual fund performance persistence. For instance, Grinblatt and Titman (1992) introduced a methodology that statistically assesses the relationship between a fund's current and past performance. They applied an extension of the Fama and MacBeth (1973) regression technique, using a regression of cross-sectional current alphas on past alphas. The null hypothesis posits that previous performance is not related to future performance, and this null hypothesis is rejected if the regression produces a significant and positive slope coefficient. Another technique was developed by Hendricks et al. (1993), who focused on measuring short-term persistence by identifying autocorrelation in mutual fund performance. They conducted a regression of fund returns on the expected return conditioned on the information available to the market in the past period. The residuals of this regression should be unpredictable. The presence of significant autocorrelation in residuals results in the rejection of the null hypothesis that past performance is unrelated to future performance.

In contrast, Kosowski et al. (2006) argued that normality assumptions may not be satisfied in the majority of fund analyses owing to several factors. First, individual stocks within typical mutual fund portfolios often exhibit returns with non-negligible higher moments, as managers tend to hold substantial positions in relatively few stocks or industries. Second, market benchmark returns may themselves be non-normal, and co-skewness in benchmark and individual stock returns can occur. Moreover, individual stocks display varying levels of time-series autocorrelations in returns. Last, funds may employ dynamic strategies that involve adjusting their levels of risk-taking in response to changes in the risk of the overall market portfolio. These issues contribute to non-normally distributed mutual fund alphas, potentially leading to inaccurate statistical inferences.

Further, Kosowski et al. (2006) introduced a novel bootstrap statistical technique as a methodology to enhance the detection of mutual fund performance persistence. The initial step involves applying an asset pricing model to estimate the actual alpha coefficients and residuals for each individual fund. Next, a time series of pseudo monthly excess returns is constructed, imposing the null hypothesis of zero true performance for each fund. When applied on each fund, these processes generate cross-sectional actual and simulated bootstrapped coefficients. If the actual alphas are higher than those observed in the bootstrap iterations, it can be concluded that luck alone is not the source of significant alphas, indicating the presence of genuine managerial skills.

This methodology offers improved inference in identifying fund managers with significant skills by accounting for differential risk-taking between funds and potential non-normalities in fund alphas (Kosowski et al., 2006). Fama and French (2010) introduced modifications to this bootstrap statistical technique. In their modified bootstrap method, they increased the number of bootstrap resampling to 10,000 times to balance out oversampling and undersampling of fund returns in a simulation run. Furthermore, they suggested bootstrapping the risk factors' returns jointly with the fund's risk premium. This modification captures any potential heteroscedasticity of the explanatory returns and disturbances of the benchmark model (Fama & French, 2010). To set the null hypothesis of no risk-adjusted return performance (alpha = 0), Fama and French (2010) subtracted each fund's alpha estimate from its monthly returns before running bootstrap simulations. The bootstrap statistical technique developed by Kosowski et al. (2006) and that by Fama and French (2010) to detect mutual fund performance persistence have significant implications in this field of study, as acknowledged in subsequent studies (A.-S. Chen et al., 2012; Harvey & Liu, 2022; Huang et al., 2023; Kooli & Stetsyuk, 2021; Riley, 2019; Tapver, 2023; Yang & Liu, 2017). These techniques provide a robust framework for more accurate evaluations of mutual fund performance persistence.

However, prior studies have yielded contradictory empirical results regarding mutual fund performance persistence. Many of these studies have found evidence supporting the hypothesis that fund managers possess genuine managerial skills. Kosowski et al. (2006), through their bootstrap approach, identified fund performance persistence and concluded that significant positive alphas cannot be solely attributed to luck, indicating that genuine stock-picking skills exist in the US market. Applying a similar bootstrap statistical technique, Kooli and Stetsyuk (2021) and Kosowski et al. (2007) found empirical evidence of genuine managerial skills in US hedge funds. In contrast, other empirical studies have found no evidence of stock-picking skills among fund managers. Fama and French (2010), through their modified approach, found that mutual funds do not possess managerial skills after accounting for their management costs. This suggests that, in some cases, any observed positive alphas may be offset by the associated costs. This methodology has also been extended to emerging markets. For instance, Tapver (2023) applied Kosowski et al.'s (2006) bootstrap technique to data for 2005–2019 from a sample of central and eastern European countries. They found that approximately 5% of active mutual fund managers in this region exhibited stock-picking skills, but these skills were only sufficient to cover their management fees. This result underscores the presence of managerial skills and their impact on fund performance.

Notably, limited evidence is available regarding mutual fund performance persistence in the Saudi Arabian market. Alsubaiei et al. (2024) and Zouaoui (2019) attempted to identify the existence of persistence in fund performance by employing a regression model that correlated one lag of performance with future performance. Alsubaiei et al. discovered a positive and statistically significant relationship, indicative of performance persistence in their sample. Conversely, Zouaoui identified a negative and significant relationship, with the exception of international funds. Recognising the importance of differentiating skills from luck and accounting for the likely non-normal distribution of individual mutual fund performance, the current study adopts the statistical bootstrap technique. Most likely, it is the first of its kind to apply the bootstrap technique on Saudi funds. Aiming to examine fund performance persistence, the study proposes the following hypotheses:

Hypothesis 3 (3.A): Managerial skills do exist among a group of active equity mutual funds in Saudi Arabia.

Hypothesis 3 (3.B): Managerial skills did exist among a group of active equity mutual funds in Saudi Arabia before the financial reforms.

Hypothesis 3 (3.C): Managerial skills do exist among a group of active equity mutual funds in Saudi Arabia after the financial reforms.

3.7 Factors Affecting Mutual Fund Performance

A substantial body of influential studies, notably those by Carhart (1997) and Grinblatt and Titman (1994), has investigated the factors that may influence the performance of mutual funds in the US market. This literature attempts to comprehend the dynamics that affect mutual fund performance. Despite the wealth of research in the US context, there is a dearth of evidence concerning the factors influencing active fund performance in the Saudi market. Furthermore, empirical insights into the factors affecting passive fund performance in Saudi Arabia are conspicuously absent. The subsequent subsections review and discuss potential factors that may influence mutual fund performance in the unique context of Saudi Arabia.

3.7.1 Investor Sentiment

Investor sentiment, a crucial aspect in understanding financial market dynamics, refers to individual investors' beliefs about future returns and risks that are not grounded in facts or economic fundamentals. Behavioural biases, such as overconfidence, conservatism and representativeness, contribute to deviations in individual investors' decision-making (Baker & Wurgler, 2007). This deviation is evident in the tendency of individual traders to base stock transactions on subjective expectations rather than objective economic factors, causing asset prices to stray from their intrinsic values (Black, 1986; Shleifer & Summers, 1990). The concept of investor sentiment was developed gradually by the BFS to explain how individuals tend to overreact or underreact to fundamental information or past returns.

Since the 1980s, the behavioural finance theory has challenged the assumptions of the TFS by positing that not all investors act with complete rationality and that psychological factors may influence investment decisions (Kahneman & Tversky, 1979; Shiller, 2003; Thaler, 1980). This evidence of definite departure from the purely economic rationale opened avenues for exploring how psychological anomalies may interfere with investment behaviours.

In the early stages of developing the concept of investor sentiment, several pioneering scholars in the finance field examined irrational effects on aggregate market returns. For instance, Shiller (1980) highlighted that the unexpected volatility in aggregate stock real dividends fails to justify the significant increase in aggregate stock index volatility. Subsequently, other scholars, including Fama and French (1988a) and Poterba and Summers (1988), provided substantial evidence of significant negative autocorrelations across US industries during extended holding periods. Furthermore, the dividend–price ratio emerged as a predictive tool for stock returns, as demonstrated by Campbell and Shiller (1988) and Fama and French (1989). Moreover, Baker and Wurgler (2007) emphasised that although these early studies did not explicitly mention investor sentiment, the predictability of stock returns reflects the correction of sentiment-induced mispricing, or time-varying risk or risk aversion that causes time variation in expected stock returns.

In subsequent research, there was a shift towards the explicit identification and quantification of investor sentiment, marking a deeper investigation of its impact on the equity market. DeLong et al. (1990) segmented market participants into sentiment-free rational arbitrageurs, who base their investments on economic grounds, and irrational traders, who are influenced by their sentiments. They posited that noise traders introduce a significant gap between market prices and intrinsic values, deterring rational investors from betting against them.

Consequently, noise traders earn higher expected unadjusted returns than risk-averse rational investors because they unknowingly bear a disproportionately higher level of risk that they themselves create. Building on this study, W. Lee et al. (2002) highlighted investor sentiment as a systematic risk in the market that influences both returns and risk. They revealed a positive correlation between excess returns and shifts in investor sentiment, and a negative correlation of these shifts with market volatility.

In addition, researchers have developed a diverse array of sentiment proxies to quantify investors' beliefs and investigate their effects on stock markets. This section reviews these proxies: First, trading volume and market turnover serve as overarching indicators of liquidity and are commonly employed as proxies for investor sentiment (Qian, 2014; Uygur & Tas, 2014). Trading volume can be seen as a measure of investors' confidence in the market, with low trading volume typically associated with declining prices and high trading volume linked to rising prices (Ying, 1966). In addition, market turnover, defined as the ratio of trading volume to outstanding shares, is another viable proxy for investor sentiment (Baker & Wurgler, 2007). Notably, some studies propose that the trading volume of individual investors provides a more accurate representation of investor sentiment (Barber et al., 2009; Kumar & Lee, 2006). Second, investor surveys have been designed to capture the perspectives of individual investors regarding the equity market. Professor Robert Shiller has developed several sentiment indices based on surveys, including the US one-year confidence index, US crash confidence index, US buy-on-dips confidence index and US valuation confidence index. These survey-based indices are widely embraced in both academic and professional circles as proxies for investor sentiment.[18] Notably, G. Brown and Cliff (2005) demonstrated that the Investors Intelligence survey can forecast market returns over the next one-

[18] Detailed information about these surveys is available at United States Stock Market Confidence Indices | Yale School of Management.

to-three years, with this investor sentiment measure capturing price deviations from intrinsic values.

Third, consumer confidence indices can serve as gauges of retail investor sentiment. The literature has presented compelling evidence of a robust association between the consumer confidence index and equity returns. Notably, Lemmon and Portniaguina (2006) and Ciner (2014) demonstrated the power of consumer confidence indices to forecast the returns on small stocks. Furthermore, a broader perspective emerged from studies that have explored the impact of the consumer confidence index on equity returns in a multi-country analysis, such as that of Hsu et al. (2011). Fourth, the flow of funds into and out of equity mutual funds indicates investor sentiment towards the equity market—inflows often signify optimism among investors, while outflows may signify pessimism. S. Brown et al. (2003) observed a significant and negative correlation between flows into bull and bear funds, underscoring a consistent pattern indicative of a strong sentiment factor among fund investors. Frazzini and Lamont (2008) leveraged mutual fund flows as a measure of investor sentiment for various stocks, finding that this metric predicts stock returns. Furthermore, Ben-Rephael et al. (2012) demonstrated a positive correlation between aggregate net exchanges of equity funds and aggregate stock market excess returns, along with a negative correlation with the volatility index.

Fifth, the discount or premium observed in closed-end funds is employed as a metric for investor sentiment. These funds issue a fixed number of shares solely traded on the secondary market. While they provide NAV as a guide, these funds are subject to trading below, or rarely above, these values. Scholars such as C. Lee et al. (1991) and Neal and Wheatley (1998) argued that the discount in closed-end funds is a suitable proxy of investor sentiment. This argument rests on the assumption that these funds are predominantly held by individual investors, given the robust correlation between the discount in the funds and stocks typically held by individual investors, such as small stocks. Moreover, there is evidence suggesting that such discounts can forecast the size premium[19] (Neal & Wheatley, 1998). Higher discounts on a closed-end fund are indicative of a pessimistic sentiment among individual investors, and conversely, lower discounts suggest a more optimistic outlook. Sixth, Baker and Wurgler (2007) proposed that option-implied volatility can serve as a proxy for investor sentiment. This view stems from the observation that options prices tend to rise in tandem with an increase in the anticipated volatility of the underlying assets. Baker and Wurgler added that the market volatility index, which measures the implied volatility, is often called the 'investor fear gauge'.

Seventh, Baker and Wurgler (2007) emphasised that it is difficult to explain extraordinary first-day returns and volumes in IPOs by factors other than investor sentiment. They presented historical IPO first-day returns and volumes that defy rational economic grounds. Moving to the eighth point, the bull–bear ratio is calculated by dividing the number of advancing shares traded by the number of declining shares traded in a given month. A bull–bear ratio exceeding 1 signifies optimism among individual investors, a ratio less than 1 indicates a pessimistic sentiment, and a ratio equal to 1 suggests a neutral stance. This metric has been utilised in various studies, including those by Bouteska (2020) and G. Brown and Cliff (2004, 2005), to discern investor sentiment trends.

Ninth, M. L. Rahman and Shamsuddin (2019) argued that excessive volatility in P/E ratios, particularly preceding market bubbles and fluctuations, signals the presence of behavioural biases. They indicated that even after accounting for fundamental factors, a non-fundamental component of the P/E ratio exhibits a significant and positive correlation with investor sentiment. In addition,

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[19] The size premium is the difference in returns between big and small firms.

Bouteska (2020) employed the P/E ratio as a proxy for investor sentiment. Last, Baker and Wurgler (2007) developed a sentiment index using six distinct proxies. They emphasised the complexity of measuring investor sentiment, noting that the most compelling tests of sentiment effects are those that employ these effects to forecast long-term returns. This assertion underscores the nature of gauging sentiment and the importance of assessing its impact over extended periods for a more comprehensive understanding.

As for the Saudi Arabian equity market, the unique dominance of individual investors sets it apart—monthly trading and ownership reports by Tadawul (2020) have revealed that a striking average of 82% of trading volume in 2010–2020 was attributable to individual traders. Their prevalence significantly surpasses that observed in developed markets. Notably, A. Rahman et al. (2015) suggested in their empirical study that individual traders in this market exhibit the characteristics of noise traders, implying a lack of rationality in their decision-making.

The dominance of noise traders in the Saudi equity market amplifies the impact of investor sentiment. Studies have examined this impact directly on individual stocks and overall market trends. Alnafea and Chebbi (2022) discovered a significant and positive impact of three sentiment proxies—average turnover rate, P/E ratio and overnight return—on stock volatility. Similarly, Altuwaijri (2016) reported a significant and positive impact of investor sentiment, measured by volume, on the returns of the main index, TASI. The findings demonstrated the sensitivity of TASI returns to investor sentiment, accounting for 3% of the returns, and the overall model could explain 13% of TASI returns.

However, mutual fund performance varies from that of the overall market portfolio owing to the influence of professional management by investment experts. On the one hand, managers' expertise significantly matters to mutual fund performance. On the other hand, the extreme participation of noise traders in the Saudi market and their ability to cause price deviations may lead to a link between investor sentiment and the performance of active and passive funds. To the best of this author's knowledge, no study has investigated the impact of investor sentiment on mutual fund performance. This gap in the literature represents a critical area for research in portfolio management. Therefore, investigating this area could offer a valuable contribution to the fields of finance and investment. Accordingly, this study proposes the following hypotheses.

Hypothesis 4 (4.A): Investor sentiment positively affects the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.B): Investor sentiment positively affects the risk-adjusted return performance of active and passive mutual funds.

3.7.2 Impact of COVID-19 Pandemic

The global outbreak of COVID-19 has ignited financial uncertainty, resulting in significant market losses and disruptions across economic sectors. Numerous studies have examined the associated impact on stock pricing behaviour worldwide (Al-Awadhi et al., 2020; Erdem, 2020; Mazur et al., 2021; M. L. Rahman et al., 2021; Xu, 2021) and have consistently revealed adverse effects on stock returns. Similarly, this pandemic has had a negative impact on the overall performance of the Saudi Arabian equity market and on that of certain individual stocks (Alzyadat & Asfoura, 2021; Atassi & Yusuf, 2021; Sayed & Eledum, 2021). However, the impact of COVID-19 on active fund performance is yet to be identified. Active mutual fund managers may have the ability to shield fund performance from the pandemic's effects owing to their skilful management strategies. However, since the specific effects of COVID-19 on mutual fund performance are ambiguous, this study aims to bridge this knowledge gap by investigating the impact of the spread of this disease on the performance of Saudi mutual funds. To this end, Chapter 8 of this thesis is dedicated to an exclusive analysis of data from the peak of the COVID-19 pandemic (March–December 2020). This dataset enables this study to discern and comprehend the pandemic's specific influence on mutual fund performance. Thus, it provides a more precise assessment of effects that do not overlap the effects of other factors that are studied over a broader time frame and that need to be excluded owing to lower data frequency.

3.7.3 Oil Price Volatility

The returns and volatility of oil prices wield a substantial influence on equity markets, with the extent of this impact hinging on whether a country is either a significant net importer or exporter in the global oil market (Park & Ratti, 2008; Wang et al., 2013). Generally, developed countries possess diversified economies such that no single industry dominates their GDP. Consequently, oil price fluctuations are less likely to significantly affect their overall equity market or the performance of equity mutual funds.

In stark contrast, Saudi Arabia, as one of the world's largest oil exporters, heavily relies on oil returns to finance a multitude of economic activities, which has fostered a unique relationship between the returns and volatility of oil prices and the performance of its equity market. Numerous studies have documented compelling evidence of the transmission of returns and volatilities between oil prices and the Saudi Arabian equity market (Almohaimeed & Harrathi, 2013; Arouri et al., 2011; Arouri & Rault, 2010, 2012; Hammoudeh & Aleisa, 2004; Zarour, 2006). This substantial influence would naturally extend to mutual fund performance. Given the limited evidence in this regard (Alsubaiei et al., 2024), this thesis builds upon prior studies by specifically focusing on locally invested mutual funds to confirm the effect of oil price volatility on both unadjusted and risk-adjusted mutual fund returns across different periods. Thus, the following hypotheses are proposed:

Hypothesis 4 (4.C): Oil price volatility negatively affects the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.D): Oil price volatility negatively affects the risk-adjusted return performance of active and passive mutual funds.

3.7.4 Fund Flow

Inflows and outflows of money play a key role in shaping mutual fund performance. Inflows occur when investors acquire units, while outflows transpire when investors redeem their units. The academic literature has extensively investigated the relationship between mutual fund performance and fund flows, yet the direction of this relationship remains a topic of debate.

The literature outlines two competing explanations for this relationship. One is the smart money hypothesis, which posits that investors possess the ability to accurately predict a fund's performance and consequently shift their investments from underperforming funds to those deemed superior. Under this hypothesis, a net cash inflow is expected to positively affect a fund's future performance (Gruber, 1996; Keswani & Stolin, 2008; Zheng, 1999). In contrast, the other, the persistent-flow hypothesis suggests that fund flows exhibit persistence. This implies that mutual funds experiencing past inflows are likely to attract additional capital, thereby increasing their assets and potentially enhancing performance. Conversely, mutual funds with past outflows are prone to further redemptions, leading to a decrease in assets and a potential deterioration in performance (G. Jiang & Yuksel, 2017; Lou, 2012; Wermers, 2003).

A substantial body of literature has revealed the positive impact of flows on mutual fund performance. Using pooled regression, Keswani and Stolin (2008) found a positive and significant impact of net aggregate flows on mutual fund performance. Similarly, Barber et al. (2016) found that after controlling for other factors, such as size, value, momentum and past performance, mutual funds with larger inflows experience above-median returns. They attributed this result to the fact that inflows can create incentives for managers to take more risks, which can lead to higher returns. Moreover, using the pooled regression technique, Alsubaiei et al. (2024) found that fund flows have positive and significant effects both on the unadjusted and the risk-adjusted return performance of mutual funds. These results support the concept of the smart money effect on mutual fund performance. In addition, G. Jiang and Yuksel (2017) confirmed a significant and positive relationship between fund flow and fund performance for a longer sample period of 1993–2014, which is driven by the persistent-flow explanation.

Other studies have documented the negative impact of flows on mutual fund performance. For instance, Edelen (1999) established a statistically significant inverse relationship between a mutual fund's abnormal returns and flows, which they ascribed to the costs incurred owing to liquidity-motivated trading. That is, mutual fund managers are obliged to raise cash for exiting investors and augment asset investments for new investors at any given time, which results in tangible costs. These trading activities impose adverse effects at the individual fund level and, consequently, on the overall mutual fund industry.

Furthermore, Frazzini and Lamont (2008) examined the relationship between US mutual fund flows and a cross-section of stock returns, as represented by risk-adjusted return. Employing a monthly ranking system based on flow, they assigned stocks into quintile portfolios. They found that mutual funds receiving the largest inflows tend to underperform the most, suggesting a pronounced 'dumb money' effect, particularly among well-known funds. Conversely, this thesis adopts the assumption of a smart money effect in the mutual fund industry in Saudi Arabia, which asserts that fund flows have a positive impact on mutual fund performance. Thus, it proposed the following hypotheses:

Hypothesis 4 (4.E): Fund flows have a positive impact on the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.F): Fund flows have a positive impact on the risk-adjusted return performance of active and passive mutual funds.

3.7.5 Management Expense Ratio

The management expense ratio is key to mutual fund return performance. This ratio includes management fees (e.g. compensation paid to managers) and operating fees (e.g. expenditure incurred for external auditing, legal services, brokerage commissions, marketing, office supplies, customer service and other administrative costs). Mutual funds deduct these fees as a percentage of total net assets to cover operating expenses (Haslem, 2009). Thus, the management expense ratio absorbs a significant amount of returns, if any.

Many studies have documented a consistent negative relationship between fund performance and the management expense ratio (Apap & Griffith, 1998; Babalos et al., 2009; Carhart, 1997; Dellva & Olson, 1998; Ferreira et al., 2013; Grinblatt & Titman, 1994; Mansor et al., 2015; Prather et al., 2004). For instance, Ferreira et al. (2013) revealed a consistent negative association between the expense ratio and mutual fund performance, across diverse countries and subsamples. In essence, mutual funds with lower expense ratios tended to outperform those burdened with higher expense ratios. Similarly, Otten and Bams (2002), who examined the impact of expense ratios on the risk-adjusted performance during 1991–1998 of mutual funds across the United Kingdom, France, Germany and the Netherlands, consistently found that this impact was negative and significant impact for all four European countries. Conversely, certain studies have observed a positive relationship between mutual fund performance and the management expense ratio (C. Chen et al., 1992; Díaz-Mendoza et al., 2014; Droms & Walker, 1996). Therefore, in the present study, it is necessary to control for fund-specific factors. Consequently, following hypotheses are proposed:

Hypothesis 4 (4.G): The management expense ratio negatively affects the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.H): The management expense ratio negatively affects the risk-adjusted return performance of active and passive mutual funds.

3.7.6 Fund Age

Studies on a fund's age, which represents the extent of its longevity in the industry, have arrived at diverse conclusions regarding its influence on mutual fund performance. These conclusions encompass positive, negative and non-significant effects.

As regards positive effects, Babalos et al. (2009) have identified a significant and positive impact of fund age on the risk-adjusted return performance of mutual funds in Greece. Similarly, Alqadhib et al. (2022), who examined the impact of fund age on the performance of 79 Saudi Arabian mutual funds during the COVID-19 pandemic, revealed that it has a positive impact on both unadjusted and risk-adjusted performance. This finding suggests that long-lived funds possess more experience regarding investment, which contributes to their positive performance.

Conversely, another group of studies has emphasised that fund age can exert a negative influence on mutual fund performance. Ferreira et al. (2013) found a significant and negative association between fund age and the risk-adjusted return performance of non-US mutual funds. Tang et al. (2012) highlighted the negative and significant impact of fund age on the benchmark-adjusted return performance of Chinese mutual funds. Further, Alsubaiei et al. (2024) also found that fund age has a negative and significant impact on the risk-adjusted performance of Saudi mutual funds. These studies posited that newer mutual funds tend to be more agile and committed to performing better in order to attract subscribers and ensure their survival, thereby exhibiting superior performance.

Nevertheless, the majority of literature asserts that fund age has no significant influence on mutual fund performance (J. Chen et al., 2004; Ferreira et al., 2013; Lou, 2012; Pollet & Wilson, 2008; Prather et al., 2004; Tang et al., 2012; Yan, 2008). Empirical evidence from studies such as that of J. Chen et al. (2004) and Ferreira et al. (2013) on the US market indicates that the impact of fund age on mutual fund performance is not statistically significant. Similarly, Tang et al. (2012), in a comprehensive study encompassing all Chinese mutual funds in their sample from 2004 to 2010, found that fund age does not have a statistically significant impact on fund performance. In light of these conflicting perspectives, the current study proposes the following hypotheses to further investigate the relationship between fund age and mutual fund performance in Saudi Arabia:

Hypothesis 4 (4.I): Fund age has a positive impact on the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.J): Fund age has a positive impact on the risk-adjusted return performance of active and passive mutual funds.

3.7.7 Compliance With Islamic Law (Shariah)

Compliance with Islamic law (shariah) is a distinctive feature of Islamic finance, embodying principles that prohibit interest (*riba*) and investments in activities such as gambling, tobacco, pornography and alcohol. Islamic mutual funds, as financial instruments adhering to the Islamic law, invest exclusively in shariah-compliant assets. Notably, more than 70% of Saudi equity mutual funds align with shariah principles. The country's legal system is fundamentally rooted in shariah, which influences various aspects of life, including business practices and investments. Given the unique nature of Islamic finance, particularly in Saudi Arabia, the performance of Islamic mutual funds has attracted attention from finance scholars. However, the impact of shariah compliance on mutual fund performance remains a subject of considerable debate within the finance field, and studies on this topic have produced contrasting results.

That is, one viewpoint in the literature is that compliance with Islamic law has a positive impact on mutual fund performance. Ashraf (2013) compared the risk-adjusted return performance in 2007–2011of Islamic and conventional funds and found that Islamic funds outperformed conventional funds, demonstrating a significant annual alpha of 1.27%. Likewise, Omri et al. (2019), who compared the performance of 14 Islamic funds with that of 22 conventional funds managed by Riyad Capital in 2009–2014, showed that the former outperformed the latter. However, it is essential to approach their results with caution owing to data collection issues, which may introduce potential biases in the findings. Their reliance on a small sample, exclusively consisting of existing funds from a single fund provider, Riyad Capital, raises questions about the generalisability of their results.

Moreover, Alqadhib et al. (2022) and Alsubaiei et al. (2024) provided further evidence from Saudi Arabia. They applied binary variables to determine differences between the performance of Islamic and conventional funds. Whereas Alsubaiei et al. (2024) only found significant higher risk-adjusted performance of Islamic mutual funds, Alqadhib et al. (2022) found that the unadjusted and risk-adjusted performance of Islamic mutual funds were both significantly higher than that of conventional mutual funds. Some studies have attributed the higher performance of Islamic mutual funds to their emphasis on riskier assets. Since these funds avoid debt-based investments, they also focus their short-term investments on equity, which is expected to provide higher returns.

Next, the other viewpoint in the literature is that compliance with Islamic law has an adverse impact on Islamic mutual funds' performance because of the restrictions on investing in certain industries and the funds' investment practices. Several studies, particularly in emerging markets, have provided evidence that conventional funds outperform Islamic funds. For example, Agussalim et al. (2017) and Zeeshan et al. (2020) compared the risk-adjusted return performance of Islamic funds with that of conventional funds in Indonesia and Pakistan, respectively and found that the latter significantly outperformed Islamic funds. In a similar comparison of Saudi mutual funds, Al Rahahleh and Bhatti (2022) used multiple measures and found that conventional funds performed better than Islamic ones throughout the sample periods studied.

Further, a third strand of the literature has asserted that compliance with Islamic law does not have a significant impact on mutual fund performance. That is, studies from this perspective have suggested that the performance of Islamic funds is comparable to that of conventional funds, indicating that investors can achieve similar investment returns while adhering to their religious beliefs. In the Saudi Arabian context, BinMahfouz and Hassan (2012), who compared the performance of Islamic funds with that of conventional funds during 2005–2010, found no statistically significant difference between their performance. They concluded that shariah compliance does not adversely affect the performance of Islamic funds and noted that these funds tend to be significantly less exposed to market risk than conventional funds. However, in this study may have the limitation of survivorship bias, for it included only existing mutual funds. Similarly, Merdad et al. (2016) found by applying both the SFM and the FFC4FM that in terms of the alpha difference, the results showed no statistically significant difference in the performance of Islamic and conventional portfolios, suggesting similar investment opportunities. In light of these findings, the present study develops the following hypotheses:

Hypothesis 4 (4.K): Compliance with shariah has positive effects on the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.L): Compliance with shariah has positive effects on the risk-adjusted return performance of active and passive mutual funds.

3.7.8 Fund Size

The influence of fund size on mutual fund return performance has been subject to diverse interpretations in the literature. One theory assumes a negative association between fund size and performance, attributing it to diseconomies of scale arising from increase in transaction costs as the fund size increases (Chan et al., 2009; J. Chen et al., 2004; Yan, 2008). Conversely, the theory of economies of scale proposes a positive association between mutual fund performance and fund size up to a certain threshold, beyond which the relationship becomes negative, forming an inverted U-shaped curve (Bodson et al., 2011; Indro et al., 1999; Perold & Salomon, 1991; Tang et al., 2012). However, some studies have found that fund size has no significant impact on mutual fund performance (Droms & Walker, 1996; Phillips et al., 2018). In the present study, fund size is measured as the natural logarithm of total net assets, and in accordance with the theory of economies of scale, the following hypotheses are proposed:

Hypothesis 4 (4.M): Fund size has a positive impact on the unadjusted return performance of active and passive mutual funds.

Hypothesis 4 (4.N): Fund size has a positive impact on the risk-adjusted return performance of active and passive mutual funds.

3.8 Chapter Summary

This chapter presented a comprehensive review of the literature on mutual funds, covering developed and emerging markets, with a specific focus on the Saudi Arabian market. By analysing prior studies this chapter has provided valuable insights into the current state of knowledge in this field. It has identified potential research gaps and builds on existing literature to formulate hypotheses. The key areas covered in this chapter include

- a discussion on the perspectives of TFS and BFS regarding mutual fund performance;
- an exploration of the development in CAPMs, which are crucial for measuring mutual fund performance;
- a review of studies that measured the actual performance of both active and passive funds;
- an examination of the literature on the persistence of mutual fund performance, which has investigated whether funds with superior performance tend to repeat their success over time or whether it is a random occurrence; and
- an overview of factors identified in prior studies that affect mutual fund performance.

Chapter 4: Research Methodology

4.1 Introduction

This chapter describes the research methodology used and the methods applied to address the research questions and accomplish the research objectives presented in Chapter 1. It also presents all the empirical models employed in this study and their applications in the literature to ensure that the hypotheses in Chapter 3 are tested through accurate approaches. In addition, this chapter provides comprehensive details about the data collection and the scope of this research, including about the sample of mutual funds, the sample period and subperiods and the frequency of the analysed data.

The first objective of this study is to identify the model that can most efficiently explain variations in mutual fund returns among the five key competing asset pricing models (Equations 4–8) available for estimating risk-adjusted performance. To facilitate this comparison, the Gibbons et al. (1989) F-test (GRS F-test) was employed. In addition, the GRS J-test and the mean absolute alpha (MAA) were utilised to further refine the results. The significance of the GRS test statistic lies in its ability to rank competing asset pricing models in terms of their capacity to explain portfolios returns (Kamstra & Shi, 2021).

The second objective of this study is to comprehensively examine the performance of both active and passive mutual funds in Saudi Arabia. To address this objective, three key assessment approaches are employed: benchmark-adjusted return performance (in Subsection 4.4.1), risk-adjusted return performance (in Subsection 4.4.2) and market timing ability (in Subsection 4.4.3). Importantly, unadjusted return is crucial to estimating all three indicators of performance.

First, unadjusted return, known as raw returns, constitute the starting point of this analysis. In this study, the computation of unadjusted return involves the use of fund logarithmic returns, as detailed in Subsection 4.2.1. This calculation is crucial as it serves as a foundational element in estimating benchmark-adjusted performance, risk-adjusted performance and market timing ability. Furthermore, unadjusted return itself also can be considered an alternative metric for reflecting mutual fund performance, a perspective shared by other studies (e.g. Alsubaiei et al., 2024; Banegas et al., 2013). Second, adjusted return performance refers to returns that have been adjusted in comparison to a corresponding return, and the consideration of certain risk factors. This performance can be further categorised into benchmark-adjusted return performance, calculated using the mean-difference measure, which is discussed in Subsection 4.2.2.1, and into risk-adjusted performance, estimated using time-series regression-based models (specifically, the SFM for passive funds and the FFC6FM for active funds). These models require the use of appropriate market proxies and a suitable risk-free rate of return, and the construction of other systematic risk factors, namely, size, value, profitability, investment and momentum, which are extensively discussed in Subsection 4.2.2.2.

Third, as for market timing models, the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model are applied to examine fund managers' market timing ability. These models can separate the performance attributable to stock selectivity skills (micro-forecasting) from that attributable to market timing skills (macro-forecasting), as discussed in Subsection 4.4.3. Last, in Section 4.5, conventional parametric tests are utilised—that is, the one- and two-sample *t*-tests and the Wald structural break test—to examine significant variations in fund performance across SMEs, and to compare the performance of active and passive mutual funds.

The third objective of the thesis involves the study of fund performance persistence—namely, whether significant mutual fund performance is attributable to genuine stock-picking skills or is merely a result of persistent good luck. To determine whether there is a group of fund managers who possess the skill to achieve consecutive significant performance, rather than relying on luck, and to account for the potential non-normal distribution of individual mutual fund performance, the application of the bootstrap statistical technique becomes necessary (Kosowski et al., 2006). Section 4.6 explains how this technique enables investigating the significance of funds' alphas while simultaneously controlling for luck-based performance.

The fourth objective of this study is to identify the influence of investor sentiment on the measured performance. Considering the substantial participation of individual traders in the Saudi Arabian market, this study introduces investor sentiment as a new market-specific factor influencing mutual fund performance. In addition, building upon existing literature, this thesis investigates the effects of factors such as oil price volatility, fund flows, management expense ratios, fund age, adherence to Islamic law (shariah) and fund size. To analyse the impact of investor sentiment and the other factors on both unadjusted and risk-adjusted fund returns, the study employs panel data regression techniques. These regressions control for both time-series and cross-sectional variations in the data (Baltagi, 2008).[20]

4.2 Measures of Mutual Fund Returns

This section explains the methods used to measure mutual fund return performance, focusing on the two main ones: the measure of unadjusted return performance and the measures of adjusted return performance. The first method primarily encapsulates the changes in mutual fund returns. Some studies have utilised this method as a performance measure of mutual funds (e.g. Alsubaiei et al., 2024; Banegas et al., 2013).

[20] The methodology specific to Chapter 8 is presented in that chapter for a more focused, detailed discussion.

The second method is the adjusted return performance (detailed in 4.2.2), which can be divided into two methods: benchmark-adjusted return measures and risk-adjusted return measures. The latter, a regression-based model, stands out as the most prevalent method employed in the literature to evaluate mutual fund performance. Meanwhile, the benchmark-adjusted return measure, which is the mean-difference approach, also holds its ground in this study field as a viable tool for assessing mutual fund performance (e.g. Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Omri et al., 2019; Zouaoui, 2019).

4.2.1 Measure of Unadjusted Returns

The unadjusted return of funds, calculated using Equation (1), is an essential element to estimate the adjusted returns in the next subsections. A modified version of Equation (1)[21] that eliminates dividends is used to calculate market returns (benchmark indices) and stocks returns (for constructing the risk factors in Equations 4–8). Equation 2 is used to calculate the standard deviations of returns. It is also used to calculate standard deviations for several other variables in the study, such as risk factors, benchmark indices and the realised volatility of oil prices.

$$R_{i,t} = ln\left(\frac{P_{i,t}+D_{i,t}}{P_{i,(t-1)}}\right) \quad (1)$$

where *R* represents fund unadjusted returns and also represents market returns and stocks returns; *ln* is the natural logarithm and *P* is the price of the i^{th} funds (fund prices are defined by their NAV), stocks and the market index at time *t*. $D_{i,t}$ is dividends for fund *i* at month *t*.

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{n}(R_t-\bar{R}_t)^2}{n-1}} \quad (2)$$

where R_t *and* $\bar{R}_t$ represent the return and the average return obtained using Equation (1), and σi represents the standard deviation of the returns.

[21] $R_{i,t} = ln(P_{i,(t-1)}/P_{i,t})$

4.2.2 Measures of Adjusted Returns

4.2.2.1 Benchmark-Adjusted Returns

The benchmark-adjusted return is measured as the difference between fund i unadjusted return ($R_{F,t}$) at time *t* and the market unadjusted return ($R_{M,t}$) at time *t*, as shown in Equation (3). This measure, which can be applied to an individual fund, compares fund returns with benchmark returns. Moreover, it can be applied to assess the aggregate performance of mutual funds, as discussed in Section 4.4.

$$\text{Mean} - \text{difference Measure} = R_{F,t} - R_{M,t} \tag{3}$$

4.2.2.2 Risk-Adjusted Returns

To calculate risk-adjusted return, it is necessary to isolate the other sources of risk that generally affect fund returns. Since mutual funds are portfolios, studies on their performance have applied regression-based models (asset pricing models) to measure these funds' risk-adjusted performance. The CAPM, which Sharpe (1964), Lintner (1965a) and Treynor (1962) developed independently, depicts the relationship between the expected returns of a portfolio and the market systematic risk. By assuming that the CAPM is empirically valid, Jensen (1968) derived Jensen's alpha—a measure of portfolio performance—through a direct application of CAPM, Equation (4) (this modified version of the CAPM is termed the single-factor model (SFM); for more details, see Section 3.3.1). The CAPM (and implicitly the SFM) has faced serious challenges; studies have identified theoretical and empirical flaws in this model and have presented substantial evidence contesting its validity (Campbell & Vuolteenaho, 2004; Fama & French, 2004; Jensen et al., 1972; Miller & Scholes, 1972; Roll, 1977, 1978). These studies proved that the CAPM fails to capture all related risk factors that affect a portfolio's expected returns. Therefore, the SFM underestimates the expected returns of portfolios, particularly those focused on value and small-cap stocks.

Next, Fama and French (1993) extended the CAPM by introducing two additional risk factors: size and value, as in Equation (5). The size factor captures the risk of the systematic outperformance of small companies over large companies, and the value factor captures the risk of the systematic outperformance of high book/market stocks on low book/market ones. The FF3FM reinforced the explanatory power of CAPM by 70–90% and generates alphas closer to zero (Fama & French, 1993). Subsequently, Carhart (1997) included momentum as a fourth factor that captures the Jegadeesh and Titman (1993) momentum anomaly as in Equation (6). The average returns of winners minus the average returns of losers capture the market anomaly of persistence in returns for firms with high or low returns in the previous year.

Later, Fama and French (2015) discovered patterns in the returns of stock portfolios related to profitability and investment that cannot be explained by the FF3FM. Therefore, they extended the FF3FM by adding two new factors to capture the risk of profitability and investment, as in Equation (7). The profitability factor captures the risk that companies with robust operating profits will exhibit systematic outperformance compared with those with weak operating profits. The investment factor captures the risk that firms that are conservative in capital investment will exhibit systematic outperformance compared with firms that are aggressive in capital investment. The FF5FM has up to 94% explanatory power (Fama & French, 2015). Last, Fama and French (2018) added the Carhart (1997) momentum factor to the FF5FM and found that it reduced the unexplained returns in portfolios' cross-sectional returns, as in Equation (8).

The current study will compare the efficiency of the SFM, FF3FM, FFC4FM, FF5FM and FFC6FM to explain the returns of mutual funds operating in Saudi Arabia. The most efficient model will be applied to measure the aggregate mutual fund performance and individual mutual fund performance in the following chapters. Accordingly, this study employs Equations (4) to (8):

$$(R_{Fi,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \varepsilon_{i,t} \tag{4}$$

$$(R_{Fi,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \beta_{i,2}SMB_{B/M,t} + \beta_{i,3}HML_t + \varepsilon_{i,t} \tag{5}$$

$$(R_{Fi,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \beta_{i,2}SMB_{\frac{B}{M},t} + \beta_{i,3}HML_t + \beta_{i,4}MOM_t + \varepsilon_{i,t} \tag{6}$$

$$(R_{Fi,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + \varepsilon_{i,t} \tag{7}$$

$$(R_{F\,i,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + \beta_{i,6}MOM_t + \varepsilon_{i,t} \tag{8}$$

In these equations, $R_{F\,i,t}$ is the unadjusted return on fund *i* for month *t* as defined in Equation (1); R_{ft} represents one-month SAMA bills (risk-free rate: SAMA treasury bills); $R_{M,t}$ is the market return defined as TASI, MSCI-SADI and S&P-SADITR; α_i represents the average abnormal returns of fund *i* over the market; and $\varepsilon_{i,t}$ represents an error term. *SMB*, *HML*, *RMW*, *CMA* and *MOM* stand for the systematic risk factors of size (small minus big), value (high minus low), profitability (robust minus weak), investment (conservative minus aggressive) and momentum (winner minus loser), respectively. The construction of these risk factors will be explained in detail in the next section. β_1 to β_6 in Equation (8) present the sensitivity of the returns of fund *i* to these risk factors. A positive (negative) and significant (non-significant) β_1 indicates a higher (lower) sensitivity to market movements; a positive (negative) and significant (non-significant) β_2 indicates a higher (lower) sensitivity to small-cap stocks; a positive (negative) and significant (non-significant) β_3 indicates a higher (lower) sensitivity to value stocks; a positive (negative) and significant (non-significant) β_4 indicates a higher (lower) sensitivity to high-profitability stocks; a positive (negative) and significant (non-significant) β_5 indicates a higher (lower) sensitivity to conservative stocks; and a positive (negative) and significant (non-significant) β_6 indicates a higher (lower) sensitivity to a higher sensitivity to winner stocks[22].

The abovementioned models are implemented via ordinary least squares (OLS) time-series regressions. The estimated intercepts of the models (alphas) are very important in the current study as these represent the risk-adjusted returns of mutual funds. Moreover, the study applies the Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors to report *t*-statistics. The Newey–West estimator is used to estimate standard errors in regression analysis and accounts for both heteroscedasticity (unequal variance) and autocorrelation (correlation between error terms) in the data. The standard errors of the estimated coefficients in a regression model are typically calculated under the assumption of homoscedasticity and no autocorrelation. However, when these assumptions are violated, the standard errors can be biased, leading to incorrect inferences about the significance of the coefficients. The Newey–West method adjusts the standard errors to account for the presence of heteroscedasticity and autocorrelation by estimating the variance–covariance matrix of the coefficients using a weighted average of the OLS estimator and a bias-corrected estimator that takes into account the correlation structure of the errors (Wooldridge, 2015). In general, the Newey–West method is widely used in econometrics and has become a standard tool for estimating standard errors in studies on mutual fund performance (e.g. BinMahfouz & Hassan, 2012; Kosowski et al., 2006).

[22] These are stocks that have experienced high increases in their prices within the past 11 months based on the Carhart (1997) model.

Subsections 4.2.2.2.1–4.2.2.2.3 explain the construction of the required variables in asset pricing models in detail. The next two subsections focus on the required independent variables: The proxies of market returns (benchmark indices) are discussed in Subsection 4.2.2.2.1, and the other systematic risk factors (*SMB*, *HML*, *RMW*, *CMA* and *MOM*) are discussed in Subsection 4.2.2.2.2. Then, Subsection 4.2.2.2.3 explains how to group mutual fund excess returns (the dependent variable).

4.2.2.2.1 Benchmark Indices

To measure mutual fund performance, an adequate benchmark index is required against which fund returns can be compared. The selection of an inappropriate benchmark index leads to biased results and inaccurate conclusions. Accordingly, this study employs three benchmark indices to analyse the unadjusted and risk-adjusted return performance of mutual funds and compares the results:

First, this study employs the TASI, which is the main index of the Saudi equity market (Tadawul). Academics usually use TASI to analyse mutual fund performance. Tadawul adopts a free-float methodology for index calculation. It also sets the maximum capping factor at 15%, which contains the weight of dominant constituents within the index. TASI is a standard index to evaluate the Saudi equity market and is calculated by Tadawul (n.d.) as shown in the following equation.

$$TASI_t = \frac{\sum_{i=1}^{n} p_{i,t} \cdot S_{i,t} \cdot C}{\sum_{i=1}^{n} p_{i,t-1} \cdot S_{i,t-1} \cdot C \pm Adj} TASI_{t-1} \quad (9)$$

where $TASI_t$ is the index value at month t, n is the number of constituents in the index, $p_{i,t}$ is the closing price of stock for constituent i at time t, $S_{i,t}$ is the number of free-float shares for constituent i at time t, C is a specified capping factor with a maximum of 15% to contain the weight of dominant constituents within the index, and Adj is the price adjustment for corporate actions on the effective date, such as bonus issues, rights issues, splits/reverse-splits/change in face value, merger/acquisition, share redemption and share cancellation.

Second, this study employs the Morgan Stanley Capital International Saudi Arabia Domestic Index (MSCI-SADI). MSCI designed this index to measure the performance of the large- and mid-cap segments of the Saudi capital market and is calculated by Morgan Stanley Capital International (2006) as shown in the following equation. This index, which has 35–40 constituents, covers approximately 85% of the free-float-adjusted market capitalisation. This study selected this index because of its distinctive characteristics compared with other indices. In fact, this market proxy can be considered a managed index because its construction methodology includes six inclusion factors.

$$MSCISADI_t = \frac{\frac{\sum_{i=1}^{n} p_{i,t} . S_{i,t} . InclusionFactor_t . Adj_t}{FXrate}}{\frac{\sum_{i=1}^{n} p_{i,t-1} . S_{i,t-1} . InclusionFactor_t}{FXrate_{t-1}}} * MSCISADI_{t-1} \tag{10}$$

where $MSCISADI_t$ is the index value at month t. $InclusionFactor_t$ represents six quality factors that determine the inclusion of a security in the index, namely, value, size, momentum, quality, yield and volatility. $FXrate$ is the fixed exchange rate of 1 USD = 3.75 SAR set by the SAMA. The other variables, $p_{i,t}$, $S_{i,t}$ and Adj are the same as in the previous index.

Third, Standard & Poor's Saudi Arabia Domestic Index Total Return (S&P-SADITR) is defined by S&P Dow Jones Indices (2023) as 'a comprehensive benchmark that is designed to define and measure the investable universe of publicly traded companies domiciled in Saudi Arabia and does not consider foreign investment limits' and is calculated by the following equation. The Total Return (TR) version, which reinvests regular cash dividends at the close on the ex-date without considering withholding taxes, has been selected for this study. Unlike TASI and MSCI-SADI, which are price-level indices, S&P-SADITR accumulates received cash dividends and accounts for their reinvestment. Therefore, S&P-SADITR accumulates higher returns than TASI and MSCI-SADI.

$$SPSADITR_t = \frac{\sum_{i=1}^{n} p_{i,t} \,.S_{i,t} \,.C + \sum_{i=1}^{n} D_{i,t}}{\sum_{i=1}^{n} p_{i,t-1} \,.S_{i,t-1} \,.C + \sum_{i=1}^{n} D_{i,t-1} \pm Adj} \; SPSADITR_{t-1} \tag{11}$$

where $SPSADITR_t$ is the index value at month t, C is a specified capping factor with a maximum of 18% to contain the weight of dominant constituents within the index, and $D_{i,t}$ is the cash dividends from issuer i at time t. The other variables, $p_{i,t}$, $S_{i,t}$ and Adj, are the same as in the previous index.

In sum, whereas TASI and S&P-SADITR cover all stocks in the market, MSCI-SADI covers the most representative stocks in the market. Moreover, MSCI-SADI and S&P-SADITR are more exposed to large firms than is TASI. The next subsection turns to other systematic risk factors in CAPMs, which are not obtainable for the Saudi market. Thus, this study needs to construct these factors.

4.2.2.2.2 Construction of Risk Factors

This section explains how the other systematic risk factors— *SMB*, *HML*, *RMW*, *CMA* and *MOM*—are constructed (i.e. the explanatory variables of mutual fund returns) of the Saudi market in a time-series form by using portfolios with specific characteristics. The Saudi market stocks are divided into 24 portfolios according to size, value (book/market), profitability, investment and momentum. Before classifying stocks, systematic filtering of firms is applied to meet stringent standards. To be included, new firms need to have at least one year of trading prices and two years of financial statements. Firms with missing data and those suspended from trading for six consecutive months in any year are excluded. Further, firms with a negative book-to-equity (B/E) ratio and special forms of companies, such as REITs, are also excluded.

The study uses the methodologies of Fama and French (1993, 2015) to construct the size, value, profitability and investment risk factors. First, it classifies stocks by their size in every June of year t. The median of market capitalisation (the sum of price*outstanding shares for all stocks) of all constituent companies determines the size of a company. Companies with a market capitalisation greater than (less than) the median are classified as large (small). Second, the study splits stocks into three categories according to their value (book equity to market equity ratio) in every December of year $t - 1$. Stocks in the top 30th percentile are classified as high, in the middle 40th percentile are classified as medium and in the bottom 30th percentile are classified as low.

Third, the stocks are classified into three categories using their profitability ratio (operating income/total shareholder equity) in every December of year $t - 1$. Stocks in the top 30th percentile, the middle 40th percentile and the bottom 30th percentile are classified as robust, medium and weak, respectively. Fourth, the study classifies stocks into three categories according to their asset growth (growth in assets in year $t - 1$ from year $t - 2$) in every December of year $t - 1$. Stocks in the top 30th percentile, the middle 40th percentile and the bottom 30th percentile are classified as aggressive, medium and conservative, respectively. The firms included in the sample are reclassified by their size, value, profitability and investment in every year.

Then, the study employs Carhart's (1997) methodologies to construct the momentum factor. First, it calculates the 11-month price returns for all firms for the month prior to the month for which it constructs momentum portfolios (see Table 4.1, equation No. 11). Then, it divides the stocks into three groups based on these price returns. Stocks in the top 30th percentile, the middle

40th percentile and the bottom 30th percentile are classified as winners, medium and losers, respectively. The study reclassifies the stocks monthly according to their 11-month returns.

The next step is to construct six portfolios from the intersection of each classification with size as a joint factor. To construct the risk factors, this study follows the 2 by 3 sorting procedures of Fama and French (1993, 2015). Portfolios returns are calculated based on value-weighted returns on a monthly basis starting from July in year *t*.[23] The value-weighted returns are used because

> using value-weighted components is in the spirit of minimising variance, since return variances are negatively related to size. More important, using value-weighted components results in mimicking portfolios that capture the different return behaviours of small and big stocks, or high- and low-BE/ME stocks, in a way that corresponds to realistic investment opportunities. (Fama & French, 1993, p.10)

Accordingly, this study forms 24 portfolios: six portfolios each are sorted based on the intersection of size–value, the intersection of size–profitability and the intersection of size–investment. Then, in line with Carhart (1997), an additional six portfolios are constructed based on the intersection of size–momentum.

The six size–value portfolios are sorted as follows: The small low portfolio produces the monthly return of the stocks that are small in size and low in value (B/M ratio); the small medium portfolio produces the monthly return of the stocks that are small in size and medium in value; the small high portfolio produces the monthly return of the stocks that are small in size and high in value; the big low portfolio produces the monthly return of the stocks that are large in size and low

[23] The analysis of this study starts from January 2010, whereas the Fama–French methodology requires portfolio formation to start in July. Hence, the study had to form the factors from July 2009 and drop these six observations.

in value; the big medium portfolio produces the monthly return of the stocks that are large in size and medium in value; and the big high portfolio produces the monthly return of the stocks that are large in size and high in value. The special equations of the risk factors are presented in Table 4.1. The value factor HML is calculated as the average of the two high B/M portfolios' returns minus the average of the two low B/M portfolios' returns (No. 3). The size–value factor $SMB_{B/M}$ is calculated as the average of the three small firm portfolios' returns minus the average of the three large firm portfolios' returns (No.7). $SMB_{B/M}$ is applied in the FF3FM in Equation (5) and the FFC4FM in Equation (6) as the size factor was structured only from size–value portfolios in the earlier study (Fama & French, 1993).

The six size–profitability portfolios are sorted as follows: The small robust portfolio produces the monthly return of the companies that are small in size and achieved strong profitability (operating profitability divided by book equity); the small medium portfolio produces the monthly return of the stocks that are small in size and achieved medium profitability; the small weak portfolio produces the monthly return of the companies that are small in size and had weak profitability; the big robust portfolio produces the monthly return of the companies that are large in size and achieved strong profitability; the big medium portfolio produces the monthly return of the companies that are large in size and achieved medium profitability; and the big weak portfolio produces the monthly return of the companies that are large in size and achieved weak profitability. The profitability factor RMW is calculated as the average of the two robust profitability portfolios' returns minus the average of the two weak profitability portfolios' returns (No. 4). The size–profitability factor SMB_{OP} is calculated as the average of the three small firm portfolios' returns minus the average of the three large firm portfolios' returns (No. 8).

The six size–investment portfolios are sorted as follows: The small conservative portfolio produces the monthly return of the companies that are small in size and conservative in asset growth; the small medium portfolio produces the monthly return of the companies that are small in size and medium in asset growth; the small aggressive portfolio produces the monthly return of the companies that are small in size and aggressive in asset growth; the big conservative portfolio produces the monthly return of the companies that are large in size and conservative in asset growth; the big medium portfolio produces the monthly return of the companies that are large in size and medium in asset growth; and the big aggressive portfolio produces the monthly return of the companies that are large in size and aggressive in asset growth. The investment factor *CMA* is calculated as the average of the two conservative portfolios' returns minus the average of the two aggressive portfolios' returns (No. 5). The size factor SMB_{Inv} is calculated as the average of the three small firm portfolios' returns minus the average of the three big firm portfolios' returns (No. 9). The final SMB is calculated as the average of the three size factors: $SMB_{B/M}$, SMB_{OP} and SMB_{Inv} (No.6). SMB is applied in FF5FM, Equation (7), and in FFC6FM, Equation (8).

For the momentum factor, six portfolios are formed: The small winner portfolio produces the monthly return of the companies that are small in size and whose stocks realised high price returns the preceding year; the small medium portfolio produces the monthly return of the companies that are small in size and whose stocks realised medium price returns the preceding year; the small loser portfolio produces the monthly return of the companies that are small in size and whose stocks realised low price returns the preceding year; the big winner portfolio produces the monthly return of the stocks that are large in size and whose stocks realised high price returns the preceding year; the big medium portfolio produces the monthly return of the stocks that are big in size and whose stocks realised medium price returns the preceding year; and the big loser portfolio produces the monthly return of the companies that are large in size and whose stocks realised high price returns the preceding year. The momentum factor *MOM* is calculated as the average of the two winner portfolios' returns minus the average of the two loser portfolios' returns (No. 10).

Table 4.2 presents summary statistics for the 24 portfolios formed to construct the risk factors. However, summary statistics for the risk factors are provided in Table 5.1 in the next chapter that discusses the analysis results. This section identified the risk factors (independent variables) for the risk-adjusted models. The next section turns to constructing mutual fund portfolios (dependent variables).

Table 4.1

Formulas for Risk Factors in Asset Pricing Models

No.	Variable	Definition	Equations
1	Fund risk premium	Asset return over the risk-free rate	$(R_{F,i,t}$ -$R_{f,i,t})$
2	Market risk premium	Market return over the risk-free rate	$(R_{m,i,t}$ -$R_{f,i,t})$
3	HML	Value factor	$(Small\ high + Big\ high)/2 - (Small\ low + Big\ low)/2$
4	RMW	Profitability factor	$(Small\ robust + Big\ robust)/2 - (Small\ weak + Big\ weak)/2$
5	CMA	Investment factor	$(Small\ conservative + Big\ conservative)/2 - (Small\ aggressive + Big\ aggressive)/2$
6	SMB	Size factor	$SMB = (SMB_{B/M} + SMB_{OP} + SMB_{Inv})/3$
7	$SMB_{B/M}$	Size factor produced in value cross-section	$(Small\ low + Samll\ Medium + Small\ high)/3 - (Big\ low + Big\ medium + Big\ high)/3$
8	SMB_{OP}	Size factor produced in profitability sorting	$(Small\ robust + Samll\ Medium + Small\ weak)/3 - (Big\ robust + Big\ medium + Big\ weak)/3$
9	SMB_{Inv}	Size factor produced in investment sorting	$(Small\ conservative + Samll\ Medium + Small\ aggressive)/3 - (Big\ conservative + Big\ medium + Big\ aggressive)/3$
10	MOM	Momentum factor	$(Small\ winners + Big\ winners)/2 - (Small\ losers + Big\ losers)/2$
11	Return for winner and loser stocks		$R_t = (P_{t-1} - P_{t-12})/\ P_{t-12}$

Table 4.2

Summary Statistics for the 24 Portfolios Used in Constructing the Risk Factors in the FFC6FM

No.	Variable	1	2	3	4	5	6
	Size–value	SL	SM	SH	BL	BM	BH
1.	*Mean*	0.0047	0.0078	0.0068	0.0032	0.0020	0.0095
	SD	0.0996	0.0847	0.0800	0.0514	0.0550	0.0629
	Size–profitability	SR	SM	SW	BR	BM	BW
2.	*Mean*	0.0079	0.0067	0.0060	0.0023	0.0072	0.0044
	SD	0.0792	0.0794	0.0972	0.0551	0.0553	0.0740
	Size–investment	SC	SM	SA	BC	BM	BA
3.	*Mean*	0.0052	0.0058	0.0096	0.0041	0.0047	0.0046
	SD	0.0907	0.0817	0.0897	0.0690	0.0554	0.0572
	Size–momentum	SW	SM	SL	BW	BM	BL
4.	*Mean*	0.0109	0.0079	0.0079	0.00733	0.0037	0.0004
	SD	0.0929	0.0830	0.1002	0.0589	0.0558	0.0674

Note. The first row presents portfolios based on the size–value characteristics. Portfolios are labelled as follows: (SL) for the portfolio that is small in size and low in value; (SM) for the portfolio that is small in size and medium in value; (SH) for the portfolio that is small in size and high in value; (BL) for the portfolio that is big in size and low in value; (BM) for the portfolio that is big in size and medium in value; and (BH) for the portfolio that is big in size and high in value. The second row presents portfolios based on the size–profitability characteristics. Portfolios are labelled as follows: (SR) for the portfolio that is small in size and robust in profitability; (SM) for the portfolio that is small in size and medium in profitability; (SW) for the portfolio that is small in size and weak in profitability; (BR) for the portfolio that is big in size and robust in profitability; (BM) for the portfolio that is big in size and medium in profitability; and (BW) for the portfolio that is big in size and weak in profitability. The third row presents portfolios based on the size–investment characteristics. Portfolios are labelled as follows: (SC) for the portfolio that is small in size and conservative in investment; (SM) for the portfolio that is small in size and medium in investment; (SA) for the portfolio that is small in size and aggressive in investment; (BC) for the portfolio that is big in size and conservative in investment; (BM) for the portfolio that is big in size and medium in investment; and (BA) for the portfolio that is big in size and aggressive in investment. The fourth row presents portfolios based on the size–momentum characteristics. Portfolios are labelled as follows: (SW) for the portfolio that is small in size and winner in momentum; (SM) for the portfolio that is small in size and medium in momentum; (SL) for the portfolio that is small in size and loser in momentum; (BW) for the portfolio that is big in size and winner in momentum; (BM) for the portfolio that is big in size and medium in momentum; and (BL) for the portfolio that is big in size and loser in momentum.

4.2.2.2.3 Construction of Mutual Fund Return Portfolios

To evaluate the efficiency of models measuring mutual fund performance in Section 4.3, and to assess mutual fund aggregate performance in Section 4.4, the study first needs to group mutual fund returns into portfolios of time-series returns in order to construct the dependent variables in Equations (4) to (8).

The study uses the equally weighted portfolio method to form the time-series returns and then subtracts the risk-free rate of return. The grouping of mutual fund returns in equally-weighted portfolios rather than value-weighted portfolios is preferred for several reasons. First, the returns of value-weighted portfolios will be tilted towards the behaviour of large mutual funds. This tilt is likely to bias the results as the returns will be affected by the behaviour of large funds (BinMahfouz & Hassan, 2012). Furthermore, the use of equal-weighted portfolio groupings is very common in the academic research on mutual fund performance (e.g. Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Merdad et al., 2010, 2016; Zouaoui, 2019). Therefore, this study follows the more proper and most common method in this area of study and groups the sample of mutual funds in equal-weighted portfolios. The next section shows how to rank competing models by their efficiency to explain mutual fund returns.

4.3 Efficiency of Models That Measure Mutual Fund Performance

This section introduces the methods used to examine the efficiency of the five competing asset pricing models (Equations 4–8) that have been introduced in Subsection 4.2.2.2 to measure the risk-adjusted returns of active funds. The study applies the GRS F-test, the GRS J-test and the MAA to rank the competing models by their efficiency in explaining mutual fund returns, and then used the most efficient model in the main analysis of risk-adjusted return performance.

The advancements in asset pricing models are substantially applicable in the research area of mutual funds. The asset pricing literature has focused on the relationship between the returns and risks of portfolios. Asset pricing models are applied to estimate mutual fund risk-adjusted return performance. Since active mutual funds' returns carry additional risks depending on their investment styles, it is important to adjust their returns for these risks to prevent the overestimation of their risk-adjusted return performance (alpha). Incorporating risk factors better explains fund returns and minimises the funds' unexplained returns (alpha) closer to zero.

As noted in the literature review in Chapter 3, asset pricing models have been developed relatively rapidly. However, the recent developments in these models have not been sufficiently reflected in studies that estimate mutual fund performance. To illustrate, only a few studies have applied the recently developed FF5FM to estimate mutual fund risk-adjusted performance in developed markets (e.g. Mustafa & Ali, 2016). Moreover, as far as known, no study has applied the FF5FM or the FFC6FM to estimate mutual fund performance in Saudi Arabia. Past studies used the SFM, FF3FM or FFC4FM by assuming these models can explain mutual fund returns efficiently (Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Merdad et al., 2016). Moreover, the asset pricing literature has investigated the explanatory power of risk factors on the returns of hypothetical portfolios (Fama & French, 1992, 1993, 2015, 2017, 2018) In contrast, this study calculates portfolios' returns by using the actual returns of mutual funds in order to investigate the explanatory power of risk factors on mutual fund returns. It applies several tests to investigate the models' efficiency in measuring mutual fund performance. The study implements the Gibbons et al. (1989) GRS F-test with the Kamstra and Shi (2020) adjustment on the model degree of freedom to examine Hypotheses 1.A, 1.B and 1.C. The study also implements the GRS J-test and MAA to enhance the results.

The GRS F-test, GRS J-test and MAA are the most commonly used methods in the literature to test the null hypothesis whether alphas from multivariate regressions are jointly equal to zero (e.g. Fama & French, 2015, 2017; Foye, 2018). The model that contains the best combination of risk factors (factors on the right-hand side) will better explain the returns of a group of portfolios (variables on the left-hand side), also known as test assets. Accordingly, the efficient model will produce the lowest GRS F-test statistic, GRS J-test statistic and MAA. Kamstra and Shi (2021) stated that the significance of the GRS test statistic in financial studies lies in its ability to rank competing asset pricing models rather than testing the original null hypothesis of the test. They added that models that result in the lowest GRS test statistics are preferred as these are considered to fit the data better. In a similar spirit, the current study applies the GRS F-test, GRS J-test and MAA to rank the competing models. The GRS F-test statistic is calculated using Equation (12). The GRS J-test statistic relaxes the assumption of normally distributed error terms and asymptotically follows the chi-squared distribution. It is calculated using Equation (13). Moreover, an alpha closer to zero is preferred as it indicates less unexplained fund returns. Therefore, the lowest MAA that is calculated using Equation (14) from the multivariate regressions also serves to determine the best model. These models are developed by Gibbons et al. (1989).

$$\text{GRS } F\text{-statistic} = \frac{T(T-N-L)}{N(T-L-1)} \; \frac{\hat{\alpha}_0' \hat{\Sigma}^{-1} \hat{\alpha}_0}{1+\bar{r}_f' \, \hat{\Omega}^{-1} \bar{r}_f} \sim F_{N,T-N-L} \tag{12}$$

$$\text{GRS } J\text{-statistic} = T \; \frac{\hat{\alpha}_0' \hat{\Sigma}^{-1} \hat{\alpha}_0}{1+\bar{r}_f' \, \hat{\Omega}^{-1} \bar{r}_f} \sim \chi^2_N \tag{13}$$

$$\text{MAA} = \frac{\sum_{i=1}^{N} |\alpha_i|}{N} \tag{14}$$

where T is the number of time-series observations, L is the number of risk factors in the model, N is the number of portfolios (variables on the left-hand side; test assets), $\bar{r}_f'$ is a vector of the sample mean of the factors (L*1), $\hat{\Omega}$ is the estimated variance–covariance matrix of the L risk factors' returns, $\hat{\alpha}'$ is the vector of estimated alphas from each time-series regression model (N*1) and $\hat{\Sigma}$ is an estimate of the residual covariance matrix of N error terms.

The study examines the models on a wide range of portfolios formed by using mutual fund returns. First, following Huij and Verbeek (2009), quantile portfolios of mutual funds are constructed based on the funds' investment styles. Thus, individual fund sensitivity to the risk factors is estimated; that is, market, size, value, profitability, investment and momentum as in Equation (8). Then, the funds are classified into three quantiles according to their sensitivity to each risk factor *i* as low, medium and high. As Table 5.2 shows, in line with these classifications, fund returns are used to construct nine portfolios (low–low, low–medium, low–high, medium–low, medium–medium, medium–high, high–low, high–medium and high–high) for each of the 15 cross-sections between factors' sensitivity (market–size, market–value, market–profitability, market–investment, market–momentum, size–value, size–profitability, size–investment, size–momentum, value–profitability, value–investment, value–momentum, profitability–investment, profitability–momentum and investment–momentum).

Last, the GRS F-test statistic, GRS J-test statistic and MAA are calculated for each set of nine portfolios for each examined asset pricing model in Table 5.3. Following Fama and French (2015), this study is not concerned whether competing models reject the null hypothesis that alphas are jointly equal to zero; rather it uses the GRS F-test statistic, GRS J-test statistic and MAA to rank these models in terms of their efficiency in explaining the excess returns of the 15 sets of mutual fund portfolios returns. The GRS F-test and GRS J-test penalise models that include explanatory variables with insufficient explanatory power. Ceteris paribus, higher unexplained variation in the dependent variable and a greater number of explanatory factors increase the value of the GRS F-test and GRS J-test statistics. Thus, the model that results in the smallest GRS test statistic is favoured as it explains portfolios' returns better (Kamstra & Shi, 2021). The model that generates the smallest MAA is also favoured as it means smaller unexplained returns. Having selected the most efficient model, this study applies it to estimate risk-adjusted return performance, which is discussed in the following section.

4.4 Analysis of Aggregate Performance of Mutual Funds

This section describes the methodologies employed to investigate the sub-hypotheses related to the second hypothesis, all of which are examined in Chapter 5. The assessment of mutual fund aggregate performance relies on three areas of performance: benchmark-adjusted return performance, risk-adjusted return performance and market timing ability.

4.4.1 Benchmark-Adjusted Return Performance

This section outlines the procedures for assessing the aggregate benchmark-adjusted return performance of active and passive funds, and subsequently comparing their performance. Hypotheses 2.A and 2.D respectively examine whether active and passive mutual funds exhibit significantly higher unadjusted returns than that of benchmark indices. First, the mutual funds' returns are formed into time-series portfolios, as outlined in Subsection 4.2.2.2.3. Then, the mean-difference measure in Equation (3) is employed to calculate the benchmark-adjusted return performance. Next, one-sample *t*-tests (as detailed in Subsection 4.5) are conducted to determine the significance of the deviation from zero. A positive and significant *t*-test result indicates superior performance, while a negative and significant result suggests inferior performance.

Furthermore, Hypotheses 2.B and 2.E respectively investigate whether there is a significant variation in the benchmark-adjusted return performance of active and passive funds during SMEs as against the overall sample period. Following the application of the mean-difference measure for both the overall sample period SMEs, a one-sample *t*-test examines the extent to which the difference significantly deviates from zero. A positive and significant (negative or non-significant) *t*-test result indicates that funds perform higher (lower or not different) during the overall sample period than during subsample periods.

Further, Hypotheses 2.C and 2.F investigate whether the inference of benchmark-adjusted return performance for active and passive funds, respectively, varies when employing different proxies of market return. Subsequent to applying the mean-difference measure, a one-sample *t*-test is used to examine the significance of the difference in deviation from zero. A significant (non-significant) *t*-test result implies that performance varies (does not vary) significantly when using different market return proxies.

Frino and Gallagher (2001) argued that indices, being non-investable and cost-free, essentially function as paper portfolios. Therefore, in line with their perspective, this study benchmarks active mutual fund returns against passive fund returns in order to investigate Hypothesis 2.G. This analysis aims to determine whether active management exhibits a significant outperformance compared with passive management when using actual investable vehicles. In this context, active funds represent active management, while passive funds represent passive management. Following the application of the mean-difference measure in equation (3), a two-sample *t*-test, as expressed in Equation (20), is employed to examine the significance of the difference in deviation from zero. A positive and significant *t*-test result suggests superior performance of active funds, whereas a negative and significant *t*-test result indicates their inferior performance. This approach enhances the understanding of how active and passive management strategies compare in terms of actual investment performance.

4.4.2 Risk-Adjusted Return Performance (Alpha)

This section outlines the procedures for conducting risk-adjusted return performance evaluations for both active and passive funds, and subsequently compares their performance. This section employs time-series regression-based models to estimate risk-adjusted return performance.

The initial step involves organising mutual fund returns into time-series portfolios, as detailed in Subsection 4.2.2.2.3.

To examine Hypothesis 2.H, the study employs the FFC6FM to estimate the aggregate risk-adjusted performance (alpha) for the active funds. Conversely, Hypothesis 2.K is tested using the SFM to estimate the aggregate risk-adjusted performance (alpha) for the passive funds, aligning with their respective investment styles. The alpha, calculated as the unexplained variation of the model and represented by the constant of the model, serves as the key metric. A positive and significant alpha indicates that mutual funds, collectively, outperform the market, adding value to their subscribers. Conversely, a negative and significant alpha suggests that mutual funds, as a whole, underperform the market.

Moreover, Hypotheses 2.I and 2.L respectively investigate whether the alphas of active and passive funds exhibit significant variations during SMEs compared with the overall sample period. Following the previous explanation on estimating the aggregate risk-adjusted performance (alpha) for active and passive funds separately, the study employs Weesie's (1999) seemingly unrelated regression method. This method allows the simultaneous estimation of alphas during SMEs and the overall sample period. Subsequently, the Wald test is applied to assess whether the difference between the estimated alphas significantly deviates from zero. A significant result from the Wald test indicates that risk-adjusted return performance during SMEs significantly varies from that during the overall sample period, while a non-significant result suggests that the observed difference is negligible. This method ensures a comprehensive evaluation of how alphas may differ between specific market conditions and the overall time frame.

Furthermore, Hypotheses 2.J and 2.M respectively investigate whether the inference of alpha for active and passive funds varies when using different proxies of market return. Following the previous explanation of estimating the aggregate risk-adjusted performance (alpha) for active and passive funds separately, the study applies Weesie's (1999) seemingly unrelated regression method. This method allows the simultaneous estimation of funds' alphas against two different proxies. Subsequently, the Wald test is employed to examine whether the difference between estimated alphas significantly deviates from zero. A significant result from the Wald test indicates that performance significantly varies when using different market return proxies. This approach ensures an understanding of how the choice of market return proxy may affect the inference drawn from alphas in the context of both active and passive funds.

Again, in line with Frino and Gallagher's (2001) perspective that indices, being non-investable and cost-free, essentially function as paper portfolios, Hypothesis 2.N is formulated to investigate the difference in estimated alphas between active funds and passive funds. To examine Hypothesis 2.N, both the SFM and the FFC6FM are applied to each type of fund for the comparative analysis between active and passive funds. Subsequently, the study employs Weesie's (1999) seemingly unrelated regression method to simultaneously estimate alphas for both active and passive funds. The Wald test is then utilised to examine whether the difference between alphas estimated by using the same model for active funds and passive funds significantly deviates from zero. A significant result from the Wald test indicates that the risk-adjusted return performance of active funds is significantly higher than that of passive funds, while a non-significant result suggests that the observed difference is negligible. This comprehensive approach ensures a robust evaluation of the divergence in risk-adjusted returns between active and passive funds.

4.4.3 Market Timing Ability

In the preceding subsection, the SFM and FFC6FM were introduced with the expectation that positive and statistically significant alphas would be estimated, signifying market outperformance by funds. However, these outcomes, if observed, can be attributed to two key factors. First, micro-forecasting skills, or stock-picking skills, involve identifying undervalued stocks for purchase and shorting overvalued ones. Second, market timing skills, or macro-forecasting skills, pertain to the ability to invest heavily in risky assets during a rising market and in defensive assets during a declining market—that is, the ability to trade based on overall market direction forecasts. Jensen (1972) conclusively established the challenge of separating the incremental performance attributable to stock-picking skills from that attributable to market timing skills using the SFM. Similar logical considerations apply to the multi-factor models in Equations (5) to (8). Consequently, various alternative models have been developed to address this challenge.

This section introduces certain specialised models designed to dissect fund performance by distinguishing between the contributions of micro-forecasting skills and market timing skills. To investigate Hypothesis 2.O, the study employs two key models for assessing the capability of mutual fund managers to time the market, namely, the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model in their original setting and within the framework of FFC6FM.

As regards the first key model, Treynor and Mazuy (1966) developed it based on the CAPM to assess the ability of fund managers to outperform the market by timing significant market fluctuations. They argued that funds should maintain a constant level of volatility over time, reflecting how well-diversified they are. When fund managers aim to enhance portfolio diversification, the returns of their portfolios tend to cluster more closely around the market line, aligning with overall market returns. However, perfect diversification is not the sole objective for most active fund managers; they also strive to make market predictions. When fund managers anticipate an impending market decline, they adjust their portfolio compositions by reallocating from high-volatility stocks to low-volatility ones, effectively reducing the portfolio's beta below 1. Conversely, when anticipating an overall market upswing, they adjust portfolios by reallocating from low- to high-volatility stocks, increasing the portfolio's beta above 1.

If fund managers accurately anticipate market movements most of the time, the linear characteristic line based on the Security Market Line may no longer be a valid model. Instead, as demonstrated in Equation (15), a quadratic characteristic line (a convex function) would be more accurate for predicting mutual fund returns, (Treynor & Mazuy, 1966). In Equation (16), the Treynor and Mazuy (1966) model is applied within the framework of the FFC6FM. A positive and statistically significant value for γ suggests the presence of managerial skill in market timing.

$$(R_{F\,i,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \gamma\,(R_{M,t} - R_{ft})^2 + \varepsilon_{i,t} \tag{15}$$

$$(R_{F\,i,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \gamma\,(R_{M,t} - R_{ft})^2 + \beta_n X_{n,t} + \varepsilon_{i,t} \tag{16}$$

where $R_{F\,i,t}$ is the fund unadjusted returns measured as in Equation (1); R_{ft} is the risk-free rate of returns, defined as the returns of one-month SAMA bills (risk-free rate: SAMA treasury bills); and α_i is the intercept of the model. This coefficient represents the selectivity skill of mutual fund managers. $\beta_{i,1}$ is the portfolio's beta or sensitivity to the market risk. γ denotes the coefficient of the market timing skills of mutual fund managers for fund *i*, and a positive and significant value of this coefficient indicates market timing ability. $R_{M,t}$ is the return of market index at time *t*, and $\varepsilon_{i,t}$ is the error term of the model with zero mean. As for the FFC6FM settings, X is a matrix of $5xt$ risk factors (size, value, profitability, investment and momentum), and β_n is a vector of 5×1 estimated coefficients. These time-series regression models are estimated using the OLS method.

Second, Henriksson and Merton (1981) built upon the CAPM and Merton's (1981) theoretical framework to develop a market timing model. The specifications outlined by

Henriksson and Merton (1981) in Equation (17) assume that mutual fund managers make forecasts regarding the market, predicting either a bull market scenario $R_{M,t} > R_{ft}$ or a bear market scenario, $R_{M,t} < R_{ft}$. In the case of a bear market forecast, $R_{M,t} < R_{ft}$, these managers would adopt a protective put option investment strategy equal to their equity market investment. The model posits that they would exercise their options during a bear market, thereby generating equivalent returns. The coefficient representing the market timing forecast is denoted as γ_t. Specifically, γ_t = 1 if the forecast made in the previous period for the current one suggests $R_{M,t} > R_{ft}$ and γ_t = 0 if the previous forecast indicates $R_{M,t} < R_{ft}$. Henriksson and Merton (1981) defined the probabilities for $\gamma(t)$ conditional upon the realised return of the market as follows: [$\gamma(t)$ = 0, | $R_{M,t} \leq R_{ft}$] and [$\gamma(t)$ = 1, | $R_{M,t} > R_{ft}$]. A positive and statistically significant γ indicates that fund managers possess the ability to accurately time the market, while a negative or non-significant γ suggests that they lack market timing skills. In Equation (18), the Henriksson and Merton (1981) model is applied within the framework of the FFC6FM.

$$(R_{F\,i,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \gamma\, max(0, R_{ft} - R_{M,t}) + \varepsilon_{i,t} \quad (17)$$

$$(R_{F\,i,t} - R_{ft}) = \alpha_i + \beta_{i,1}(R_{M,t} - R_{ft}) + \gamma\, max(0, R_{ft} - R_{M,t}) + \beta_n X_{n,t} + \varepsilon_{i,t} \quad (18)$$

where $R_{F\,i,t}$ is the fund unadjusted returns measured as in Equation (1), R_{ft} is the risk-free rate of returns defined as the returns of one-month SAMA bills, and α_i is the intercept of the model, estimated through OLS regression analysis. This coefficient represents the selectivity skill of mutual fund managers; $\beta_{i,1}$ and γ respectively are the portfolio's beta or sensitivity to the market risk, and the coefficient of market timing skills of these managers for fund *i*, estimated using OLS regression analysis. $R_{M,t}$ is the return of market index at time t, and $\varepsilon_{i,t}$ is the error term of the model with zero mean. As regards the FFC6FM settings, X is a matrix of 5xt risk factors (size, value, profitability, investment and momentum), and β_n is a vector of 5×1 coefficients. These time-series regression models are estimated using the OLS method.

4.5 Other Parametric Test Statistics

This section presents several parametric test statistics utilised in the thesis for hypothesis testing, including the one-sample *t*-test, the two-sample *t*-test and the Wald test. It also explains the purpose for which each test is utilised.

4.5.1 One-Sample *t*-Test

The one-sample *t*-test is a statistical hypothesis test that compares the mean of a sample to a known or hypothesised value. A *t*-statistic is calculated, as in Equation (19), representing the difference between the sample mean and the hypothesised mean relative to the variability in the sample. The *t*-statistic is then compared with a *t*-distribution with degrees of freedom equal to the sample size minus one, and a *p*-value is calculated to determine the probability of obtaining the observed result by chance. If the calculated *t*-statistic is more extreme than the critical value, the null hypothesis (H0: $\mu = \bar{x}$) is rejected, indicating a significant difference between the sample mean and the hypothesised mean. Conversely, if the *t*-statistic is not more extreme than the critical value, the null hypothesis is not rejected, and it is concluded that there is no significant difference.

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}} \tag{19}$$

where $\bar{x}$ is the mean of a tested sample, μ is the hypothesised mean value, s is the sample standard deviation and n is the sample size.

4.5.2 Two-Sample *t*-Test

The two-sample *t*-test is a statistical hypothesis test employed to assess whether there is a significant difference between the means of two independent samples. This test is particularly useful when comparing the means of two groups, in determining the statistical significance of observed differences. The test involves calculating the *t*-statistic, as shown in Equation (20), which represents the ratio of the difference between the two sample means to the standard error of the difference. The resulting *t*-value is then compared with a *t*-distribution with degrees of freedom equal to the sum of the sample sizes minus two. If the calculated *t*-statistic is more extreme than the critical value, the null hypothesis (H0: μ1=μ2) is rejected, indicating a significant difference between the means of the two independent samples. Conversely, if the *t*-statistic is not more extreme than the critical value, there is insufficient evidence to reject the null hypothesis, and it is concluded that there is no significant difference between the means of the two samples.

$$t = \frac{x1 - x2}{S\sqrt{\frac{1}{n1}+\frac{1}{n2}}} \tag{20}$$

where $X1$ and $X2$ are the sample means of the two independent samples, *S* is the pooled standard deviation, and *n1* and *n2* are the sample sizes of the two samples.

4.5.3 The Wald Test

The Wald (1943) test is a versatile statistical test used to examine linear restrictions on coefficients within a regression model. It is often employed to assess whether a single coefficient is equal to a specified value or whether a group of coefficients is jointly equal to certain values. For instance, in a test for the equality of two coefficients, the null hypothesis is stated as H0: $\hat{\beta}_1 = \hat{\beta}_2$. The resulting W-value is then compared with a chi-squared distribution with one degree of freedom. If the W-value is more extreme than the critical value from the chi-squared distribution, the null hypothesis is rejected, leading to the acceptance of the alternative hypothesis that the coefficients are not equal. The equation for the Wald statistic is given by:

$$W = \frac{(\hat{\beta}_1 - \hat{\beta}_2)^2}{Var(\hat{\beta}_1) + Var(\hat{\beta}_2) - 2 \cdot Cov(\hat{\beta}_1, \hat{\beta}_2)} \quad W \sim \chi_1^2 \qquad (21)$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$are the estimated coefficients, and Var, Cov and are the variance and covariance of the estimated coefficients, respectively.

4.6 Persistence of Mutual Fund Risk-Adjusted Performance

The previous sections discussed the methodologies for analysing aggregate mutual fund performance. This section focuses on the methodologies for examining the persistence of mutual fund risk-adjusted performance. As regards the aggregate mutual fund performance, funds with significantly positive alphas may balance out funds with significantly negative alphas. In this case, it is crucial to distinguish skill from luck, that is, whether funds with superior performance consistently outperform the market and whether those with inferior performance consistently underperform. The literature has embraced various approaches to test mutual fund risk-adjusted performance persistence. For instance, Grinblatt and Titman (1992) extended the Fama and MacBeth (1973) regression technique to regress cross-sectional current alphas on past alphas. Hendricks et al. (1993) measured short-term persistence by detecting autocorrelation in mutual fund performance. The presence of significant autocorrelation in residuals resulted in the rejection of their null hypothesis that past performance is unrelated to future performance. However, the inference of persistence in past methods could be biased because of potential non-normality in individual fund alphas (Kosowski et al., 2006).

Therefore, Kosowski et al. (2006) introduced a bootstrap statistical technique, which is the latest, reliable method to distinguish persistence in mutual fund performance. This approach investigates luck versus skill in the cross-section of mutual fund risk-adjusted return performance. The methodological procedures for investigating mutual fund performance persistence include two main steps: estimating the actual alpha and t-statistics for each individual fund and simulating the alpha and t-statistics for each. If the actual alphas or t-statistics have much more extreme positive values than those in the bootstrap iterations, it can be concluded that luck is not the sole source of significant performance, and real skills exist. Kosowski et al. (2006) built on Efron and Tibshirani's (1994) study to develop a bootstrap simulation technique that can be applied to investigate luck versus skill in the cross-section of mutual fund risk-adjusted return performance. This technique has had significant implications on the area of persistence in mutual fund performance because of its reliability. It stands out over other methods because it accounts for differences in risk-taking among funds, and non-normality in individual fund alphas (Kosowski et al., 2006). Fama and French (2010) introduced further modifications to this approach. Overall, the bootstrap statistical technique yields more appropriate inference of persistence in mutual fund risk-adjusted return performance and has significant application in this area of study.

In the bootstrap method of Kosowski et al. (2006), first, estimate the actual coefficients using the FFC6FM for each fund separately. That means, for fund i, estimate the coefficients of alphas, the t-statistic of alphas, factor loadings ($\hat{\alpha}_i$, $\hat{t}_{\hat{\alpha}_i}$, $\hat{\beta}_{i,1}$, $\hat{\beta}_{i,2}$, $\hat{\beta}_{i,3}$, $\hat{\beta}_{i,4}$, $\hat{\beta}_{i,5}$, $\hat{\beta}_{i,6}$) and time-series residuals ($\hat{\varepsilon}_{i,t}, t = T_{i0}, \ldots, T_{i1}$) where $T_{i0}\ and\ T_{i1}$ are the first and last month. Second, from the original fund residuals draw a sample with replacements to create a pseudo time series of the resampled residuals ($\hat{\varepsilon}^{b}_{i,t_\epsilon}$,$t_\epsilon = s^{b}_{T_{i0}}, \ldots, s^{b}_{T_{i1}}$), where b is an index for the bootstrap number (b = 1 for bootstrap resample number 1) and each of the time indexes $s^{b}_{T_{i0}}, \ldots, s^{b}_{T_{i1}}$ are drawn randomly from $T_{i0}\ and T_{i1}$. This procedure reorders the original sample of $T_{i1} - T_{i1} + 1$ residuals for fund i. Significantly, Kosowski et al. (2006) retained the original chronological ordering of the risk factors (not resampled). Next, by imposing the hypothesis of zero true performance (α_i= 0, or, equivalently, $\hat{t}_{\hat{\alpha}_i}$ = 0), the pseudo monthly excess returns $R_{i,t}^{b}$ for each fund are regressed on the factors, as in Equation (22).

$$R_{i,t}^{b} = \beta_{i,1}MRP_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + \beta_{i,6}MOM_t + \hat{\varepsilon}_{i,t_\varepsilon}^{b} \quad (22)$$

where $t = T_{i0}, \ldots, T_{i1}$ and $t_\epsilon = s_{T_{i0}}^{b}, \ldots, s_{T_{i1}}^{b}$.

In contrast to this procedure, in the Fama and French (2010) bootstrap procedure, the risk factor returns and the residuals for all funds are jointly resampled. Fama and French (2010) suggested that this jointly resampling would capture the correlated heteroscedasticity of the explanatory factors and disturbances of a benchmark model, if any. Moreover, they argued that bootstrap sampling of 10,000 times instead of 1,000 times as in Kosowski et al. (2006) should balance out the oversampling and undersampling of fund returns in a simulation run. Last, Fama and French (2010) imposed the hypothesis of no abnormal performance by deducting the actual alpha coefficient from each of the pseudo monthly excess returns for each fund and then regressed these on the risk factors, as in Equation (23). Therefore, the present study will apply the resampling procedures of Fama and French (2010), which allows a discussion of its findings with those of the most recent studies.

$$[R_{i,t} - \hat{a}]^{b} = \beta_{i,1}MRP_{t_\varepsilon}^{b} + \beta_{i,2}SMB_{t_\varepsilon}^{b} + \beta_{i,3}HML_{t_\varepsilon}^{b} + \beta_{i,4}RMW_{t_\varepsilon}^{b} + \beta_{i,5}CMA_{t_\varepsilon}^{b} + \beta_{i,6}MOM_{t_\varepsilon}^{b} + \hat{\varepsilon}_{i,t_\varepsilon}^{b} \quad (23)$$

Although Equations (22) and (23) impose a zero alpha by construction, regressing the returns for a given bootstrap sample *b* on the FFC6FM may result in a positive estimated alpha (and *t*-statistic) as the bootstrap may have drawn an abnormally high number of positive residuals.

Conversely, the model may yield a negative estimated alpha (and t-statistic) if the bootstrap has drawn an abnormally high number of negative residuals (Kosowski et al., 2006).

Accordingly, this study applies t-statistics for constructing bootstrapped cross-sectional distributions because t-statistics possess advantageous statistical properties compared with alpha itself (Kosowski et al., 2006). To illustrate, some funds have a shorter lifetime than others, and their risk-taking levels differ, both of which lead to high variance-estimated alpha distribution. Accordingly, the high variance will bias the produced alphas of these funds (S. Brown et al., 1992). Therefore, Kosowski et al. (2006) suggested constructing bootstrapped cross-sectional distributions based on t-statistics because they scale alphas by their standard errors. Therefore, to examine Hypotheses 3.A, 3.B and 3.C in Chapter 6, the study repeats the above resampling procedures for all funds i = 1,..,N, until arriving to a draw from the cross-section of bootstrapped alphas ($\hat{a}_i^b, i = 1, \dots, N$) and their t-statistics $\hat{t}_{\hat{\alpha}_i}^b, i = 1, \dots, N$. Then these t-statistics are ranked from the lowest to the highest to create luck distributions. Similarly, the t-statistics of the actual alphas are ranked from the lowest to the highest. Under the null hypothesis of the existence of stock-picking skills, this study assumes that the extreme tail of the cross-sectional distribution of the t-statistics of the actual alphas exceed the extreme tail of the cross-sectional distribution of the t-statistics of the bootstrapped alphas. Therefore, if those bootstrap iterations generate far fewer extreme positive values of $\hat{t}_{\hat{\alpha}}$ than those observed in the actual estimations, it can be concluded that luck is not the sole source of genuine alphas, and real skills exist.

4.7 Factors That Affect Mutual Fund Performance

This section outlines the methodology for identifying factors that may affect the performance of mutual funds, encompassing both unadjusted return and risk-adjusted returns. In order to identify the impact of these factors in Chapter 7, panel data analysis techniques are employed. While some of these factors have been extensively examined in the context of developed markets, evidence of their influence on Saudi mutual funds is limited. This study introduces investor sentiment as a new factor, alongside the examination of oil price volatility, compliance with Islamic law (shariah), management expense ratio, fund flows, fund age and fund size. Table 4.3 summarises the dependent and independent variables. Since dependent variables have been defined previously, the study will define the independent variables and provide a brief justification for their potential influence on mutual fund performance.

Table 4.3

Description of Dependent and Independent Variables Used in the Main Analysis

Panel A: Dependent variables	Proxy	Measurement
1.Unadjusted return	Unadjusted return	Natural logarithm of recent price and any dividends divided by the previous month price; see Equation (1).
2.Risk-adjusted return	Risk-adjusted return	Estimated alpha of the SFM for passive funds and FFC6FM for active funds; see Equations (4) and (8).
Panel B: Independent variables	**Proxy**	**Measurement**
1. Investor sentiment	• Trading volume	Natural logarithm of total traded shares by individual investors.
	• Market turnover	The ratio of number of shares traded by individual investors divided by number of free-float shares.
	• Average price–earnings ratio	The average price–earnings ratio for all firms in the market.
	• Bull–bear ratio	Number of advancing shares traded divided by number of declining shares traded in a specific month.
	• IPCSI-SA	A national survey-based index calculated by Ipsos Saudi Arabia.
2. Oil price volatility	Realised volatility	Natural logarithm of Equation (2)—monthly standard deviation based on oil daily returns.
3. Fund flows	Net flow	See Equation (24).
4. Management expense ratio	Expense ratio	Management fee plus operating expenses.
5. Fund age	Year	Total years since inception of fund.
6. Fund size	Total net asset	Natural logarithm of total net asset.
7. Compliance with Islamic law	Categorical variables	Assign 1 for Islamic funds and 0 for conventional funds.

Note. Data are in monthly form and were collected from the Refinitiv Datastream database.

4.7.1 Investor Sentiment

As discussed in the literature review, extensive evidence supports the impact of investor sentiment on stock markets globally, reflecting deviations in asset prices stemming from biases in irrational investors' beliefs about future returns and risks, which are not grounded in economic fundamentals. In developed markets, such as the US and Europe, individual traders contribute to 10% and 5% of the total market trading volume, respectively (Adinarayan, 2021). In stark contrast, the Saudi market showcases a distinctive trend, with individual traders comprising an average of 82% of the monthly trading volume in 2010–2020 (Tadawul, 2020), reflecting their dominant role in this market. Investor sentiment serves as a widely adopted metric to capture the noisy expectations of individual traders, and it has a substantial impact on Saudi market performance and volatility (Alnafea & Chebbi, 2022; Altuwaijri, 2016).

Although mutual fund performance typically varies from market performance owing to the expertise of professional managers, investor sentiment is likely to influence mutual fund performance. This possibility arises owing to the substantial participation of individual traders in the Saudi market, who have the capacity to induce fluctuations in asset prices, as revealed in empirical evidence about the impact of investor sentiment on Saudi market performance and volatility (Alnafea & Chebbi, 2022; Altuwaijri, 2016). This thesis assumes that investor sentiment positively affects mutual fund unadjusted return performance and risk-adjusted return performance. Therefore, it employs five individual proxies of investor sentiment: market trading volume, market turnover, bull–bear ratio, average price/earnings ratio, and the Ipsos Primary Consumer Sentiment Index – Saudi Arabia (IPCSI-SA).

First, the market trading volume is measured as the natural logarithm of the volume of trades in a specific month (this study only considered the volume of trades by individual investors).

An increase (decrease) in the trading volume indicates that individual investors are optimistic (pessimistic). Second, the market turnover is measured as number of shares traded by individual investors divided by the total number of free-float shares in a specific month. An increase (decrease) in the market turnover indicates that individual investors are optimistic (pessimistic). Third, the market average P/E ratio is measured as the average share price divided by the earnings per share for all firms in the market. An increase (decrease) in the P/E ratio indicates that individual investors are optimistic (pessimistic). Fourth, the bull–bear ratio is measured as the number of advancing shares traded divided by the number of declining shares traded in a specific month. If this ratio is above one, below one and equal to 1, it indicates that individual investors are optimistic, pessimistic and neutral, respectively. Fifth, the IPCSI-SA is a comprehensive national survey-based index that gauges consumer attitudes across four main aspects: current personal financial conditions, economic expectations, investment climate and employment confidence (Ipsos, 2022).[24]

4.7.2 Oil Price Volatility

Limited research has been conducted on the impact of oil price volatility on mutual fund performance. Alsubaiei et al. (2024) presented evidence of its negative impact on mutual fund unadjusted and risk-adjusted performance. This impact reflects the strong link between the Saudi Arabian equity market and oil market. Building on Alsubaiei et al.'s (2024) study, this study measures monthly realised volatility of oil prices using the natural logarithm of oil returns standard deviation. Alsubaiei et al. argued that realised volatility, computed using the S&P GSCI crude oil excess return, provides more precise estimations of oil price volatility because it is closer to being normally distributed.

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[24] These proxies of investor sentiment and their applications in prior studies have been discussed extensively in Chapter 3.

4.7.3 Fund Flows

The literature has offered two competing explanations of the relationship between mutual fund performance and fund flows. The 'smart money' hypothesis assumes that investors can predict fund performance and thus reallocate their investments from underperforming funds to outperforming funds. Under this hypothesis, net cash flow is expected to positively influence a fund's future performance (Gruber, 1996; Keswani & Stolin, 2008; Zheng, 1999). Conversely, the persistent-flow hypothesis suggests that fund flows exhibit persistence, that is, mutual funds with past inflows are likely to attract further capital, thereby enhancing their existing assets and performance, and funds with past outflows are likely to experience further redemptions, diminishing assets and deteriorating performance (G. Jiang & Yuksel, 2017; Lou, 2012; Wermers, 2003). This thesis adopts Equation (24) as the conventional model in the literature to measure fund flows, drawing from established methodologies (Crane & Crotty, 2018; Ferreira et al., 2013; James & Karceski, 2006; Kacperczyk et al., 2008).

$$Fund\ flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}} \tag{24}$$

where $Fund\ flow_{i,t}$ is the change in the percentage of a fund's money flow through month t, TNA is the total net assets (size) of fund i and R is the fund's returns including the capital gains and dividends it receives during month t.

4.7.4 Management Expense Ratio

The management expense ratio is a pivotal factor influencing mutual fund return performance and represents a percentage of the total net assets. This comprehensive metric encapsulates various fund expenses, encompassing management fees (e.g. compensation for the manager and investment team members) and operating fees ((e.g. expenditure incurred for external auditing, legal services, brokerage commissions, marketing, office supplies, customer service and other administrative costs). The management expense ratio absorbs a portion of returns. While the literature has commonly established a negative relationship between funds' performance and their management expense ratio (Carhart, 1997; Ferreira et al., 2013; Grinblatt & Titman, 1994), Alsubaiei et al. (2024) observed that funds charging a higher management expense ratio tend to perform better.

4.7.5 Fund Age

The age of a fund dictates its longevity in the market, sparking debates on whether it positively or negatively influences fund performance. One perspective suggests that long-standing funds possess extensive investment experience, fostering a positive relationship between age and performance. Conversely, others argue that newer funds, driven by enthusiasm, strive for superior performance to attract a larger subscriber base. Empirical results have yielded three perspectives on the relationship between fund age and performance: positive (Alqadhib et al., 2022), negative (Alsubaiei et al., 2024; Ferreira et al., 2013) and no relationship (Carhart, 1997; J. Chen et al., 2004; Tang et al., 2012). Following past studies, in this study, fund age is quantified as the natural logarithm of the fund's age in years.

4.7.6 Fund Size

The literature has revealed multifaceted effects of fund size on mutual fund return performance. One theory suggests a negative relationship, attributing it to diseconomies of scale as transaction costs escalate with size (Chan et al., 2009; J. Chen et al., 2004; Yan, 2008). Conversely, the economy of scale theory suggests a positive relationship, contending that larger funds often reduce expenses, leading to enhanced performance. This theory describes a dynamic whereby performance increases with size, up to a certain point before the relationship turns negative (Bodson et al., 2011; Indro et al., 1999; Perold & Salomon, 1991; Tang et al., 2012). Fund size is measured as the natural logarithm of the total net assets (i.e. AUM).

4.7.7 Islamic Law Compliance

Compliance with Islamic law is considered a crucial factor that affects mutual fund performance. Shariah-compliant funds have a supervisory board to ensure adherence to Islamic law in their holdings. Although such adherence is preferred in Islamic-majority countries, it does not guarantee superior performance. The literature has yielded varied conclusions: Some studies have indicated that the performance of Islamic funds is superior (Alqadhib et al., 2022; Ashraf, 2013; Merdad et al., 2016), others have suggested it is inferior (Al Rahahleh & Bhatti, 2022; Zeeshan et al., 2020) and some have found no performance difference (Alsubaiei et al., 2024; BinMahfouz & Hassan, 2012). The study proxies for compliance with Islamic law using categorical effects (dummy variables), assigning 1 to Islamic funds and 0 to conventional funds, assuming that compliance with Islamic law has a positive impact on fund performance.

After measuring all the independent factors, the study employed panel data analysis to investigate the impact of investor sentiment and other factors on the unadjusted return performance and risk-adjusted return performance of funds. This analysis controls for both time-series and cross-sectional variation, minimising estimation bias from potential issues, such as heteroscedasticity and multicollinearity (Baltagi, 2008). To determine the best approach for estimating Equation (25), the study conducted standard procedures of model selection tests. These tests are the Chow (1960) test for comparing pooled OLS models and fixed-effect models, the Breusch and Pagan (1980) Lagrange multiplier test for comparing pooled OLS models and random-effect models and the Hausman (1978) test for comparing fixed-effect and random-effect models. These model selection tests indicated that the pooled OLS regression estimation approach is the most appropriate for investigating the impact of factors on mutual fund performance. Each proxy of investor sentiment is individually regressed on fund returns, and subsequently, these regressions are conducted in conjunction with other factors. A simple comparison will be used to identify the difference in the impact on active and passive funds.

$$Fund\ Retun_{i,t} = \alpha + \beta_1 investor\ sentiment_{i,t-1} + \beta_2 oil\ price\ volatility_{t-1} + \beta_3 flow_{i,t-1} + \beta_4 management\ expense\ ratio_i + \beta_5 fund\ agei_{i,t} + \beta_6 fund\ size_{i,t} + \beta_7 SC_i + \varepsilon_{i,t} \tag{25}$$

where $Fund\ Retun_{i,t}$ is the responding variable defined as the unadjusted return and estimated risk-adjusted returns for fund *i* at time *t*. Fund unadjusted return performance is measured as the natural logarithm of compounded fund returns, as in Equation (1). Fund risk-adjusted return performance is a fund's unexplained returns over the market returns and other risk factors estimated using the SFM in Equation (4) for passive funds and the FFC6FM in Equation (8) for active funds. Fund risk-adjusted returns is measured as the sum of the estimated constant and estimated residuals of the models. $Investor\ Sentiment_{i,t-1}$ is the investor sentiment proxy *i* at time *t-1*. A significant coefficient indicates that the return of the fund *i* is sentiment driven. *Management expense ratio* is fund *i's* annual management costs, operating fees and subscription fees if any. $Flow_{i,t-1}$, denotes the percentage of monthly net inflows and outflows for fund *i* at time *t-1* as calculated using Equation (24). *Size* is the size of fund *i* in period *t*, which is defined as the natural logarithm of total net assets; *age* is defined as the age of fund *i* in years. *Oil volatility* is the one-lag monthly realised volatility of oil prices based on daily prices. *SCi* is a dummy variable that equals 1 for shariah-compliant funds and 0 otherwise for each fund. Last, $\varepsilon_{i,t}$ represents an error term. This model determines the relationships between the returns of funds and the independent variables. This model will examine the sub-hypotheses of Hypothesis 4 by testing whether $\beta i \neq 0$. If $\beta i = 0$, it indicates that there is no relationship between the variable and fund performance.

4.8 Data and Scope of Research

This study collected the required data from various secondary data sources. The main data, such as fund net asset values (fund trading prices), index prices and financial ratios, were obtained from the Refinitiv Datastream database. Additional data, including funds' financial statements, funds' terms and conditions and other supplemental data, were acquired from the Tadawul website. The risk-free rate of returns, represented by the returns of one-month SAMA bills, was sourced from the Saudi Central Bank website. Data related to the impact of COVID-19 on mutual fund performance, such as the number of confirmed cases and fatalities in Saudi Arabia, were obtained from the Ministry of Health's COVID-19 daily report.

This study covers all locally invested mutual funds in the Saudi Arabian capital market. The sample is drawn from all of the 327 funds that have ever existed in Saudi Arabia (254 existing and 73 liquidated). The study focuses on Saudi active and passive mutual equity funds. Hence, it excludes non-equity funds, funds that do not invest locally, consolidated funds and charitable endowment funds. Existing and liquidated mutual funds are both included in the sample to account for survivorship bias, resulting in a final sample of 120 active equity funds and 14 passive equity funds. Mutual funds are categorised as active or passive according to their descriptions in funds' terms and conditions. ETFs are included in the sample of passive funds to generalise estimations for passive management, following the conventional approach in the literature (Crane & Crotty, 2018).

The overall analysis covers the period from 1 January 2010 to 31 December 2020. Subsample periods include the financial crisis periods from September 2014 to September 2016, and from May 2019 to December 2020 (both financial crises were combined in the analysis), the period before the 2015 financial reforms from January 2010 to June 2015, the period after the 2015 financial reforms from July 2015 to December 2020, bull market periods when the stock market was observed to be bullish and bear market periods when the stock market was observed to be bearish. Monthly data are utilised for the primary analysis, providing a maximum of 132 time-series return observations for each fund. An additional subsample period is analysed separately using weekly data, namely, the period of the COVID-19 pandemic in Saudi Arabia from 5 March to 31 December 2020. The statistical software program Stata was used to analyse data and produce the results.

4.9 Chapter Summary

This chapter described the research methodology and the methods applied to fulfil research objectives outlined in Chapter 1. The chapter detailed the statistical methods and econometric models that will be employed to examine the hypotheses and answer the research questions. It also explained why these methods and models are suitable for this analysis by linking current applications to the related past literature to ensure that the hypotheses in Chapter 1 are tested through accurate approaches. In addition, the chapter offered comprehensive details on the data collection and the scope of research, covering the sample of mutual funds, the study period, subperiods and the frequencies of analysed data.

Chapter 5: Mutual Fund Return Performance

5.1 Introduction

This chapter presents and discusses the results related to two main hypotheses outlined in Chapter 3. The first hypothesis aims to identify the most efficient model that explains mutual fund performance in Saudi Arabia more effectively, encompassing recent models that probably have not been applied earlier to examine mutual fund performance. The analysis focuses on how well asset pricing models explain mutual fund returns, with the aim of ranking the models based on their efficiency in explaining mutual fund performance. The efficiency of models in explaining mutual fund returns is assessed based on their accuracy in measuring unexplained returns (alpha). This study compares five asset pricing models: SFM, FF3FM, FFC4FM, FF5FM and FFC6FM. This investigation contributes to the literature on asset pricing models by testing these models on actual portfolio returns.

The second hypothesis evaluates the performance of active and passive funds across the overall sample period and during the subsample periods of SMEs, exploring whether mutual fund performance during SMEs varies from that during the overall sample period. It also compares the performance of active funds to that of passive funds. In addition, it examines the impact of using different market indices as proxies for market returns on the inference of mutual fund performance. Last, it assesses the ability of equity mutual fund managers to time the market. The findings contribute to the broader discussion in the finance literature by exploring the inconsistencies between the TFS and the BFS as regards mutual fund performance.

The remainder of this chapter is structured as follows: Section 5.2 presents and discusses summary statistics, providing insights into the descriptive statistics of variables used in the main analysis. Section 5.3 discusses the results from tests on the efficiency of models that measure mutual fund performance. Section 5.4 presents and discusses the results of mutual fund performance using different approaches and explores variations during the overall sample period and SMEs. The concluding section summarises the chapter.

5.2 Summary Statistics of Main Variables

This section presents and discusses the statistics of variables central to the main analysis across the overall sample period. Table 5.1 provides descriptive statistics for the variables incorporated in Equations (4) to (8), encompassing the risk premiums of both active and passive funds (as dependent variables), as well as market risk premiums and other risk factors (independent variables).

Table 5.1 reveals that the average risk premiums for active and passive funds were 0.523% and 0.099%, respectively. The positive average risk premium across all three market indices is noteworthy. Specifically, S&P-SADITR demonstrated returns twice that of TASI and MSCI-SADI, potentially attributable to the compounding returns from reinvesting dividends. TASI, MSCI-SADI and S&P-SADITR recorded risk premiums of 0.201%, 0.241% and 0.469%, respectively.

In Table 5.1, the presence of a positive size risk factor (*SMB*) in the Saudi equity market indicates that, on average, small-sized firms outperformed larger-sized firms by 0.215% in terms of returns. Furthermore, the positive value risk factor (*HML*) suggests that high-value firms outperformed low-value firms by an average of 0.415%. Conversely, the negative profitability risk factor (*RMW*) points to a performance gap, indicating that high-profit firms underperformed low-profit firms by an average of −0.030%. Similarly, the negative investment risk factor (*CMA*) suggests that conservative investment firms underperformed aggressive investment firms by an average of −0.248%. Last, the positive momentum risk factor (*MOM*) highlights that high-market-return firms outperformed low-market-return firms by an average of 0.491%. Further discussions regarding these factors are provided in subsection 5.4.2.1.1.

The additional statistics in Table 5.1 offer insights into the reliability of regression analyses. For instance, the independence of variable observations (serial correlation) is a key assumption in OLS regressions. The results of the autocorrelation function demonstrate no significant serial correlation for lags 1, 2 and 12. Moreover, multicollinearity, another potential concern in OLS regression models, is not an issue as the statistics show low correlations between independent variables. To further assure the reliability of this analysis, the study will report the variance inflation factor (VIF) to detect any potential multicollinearity. Significantly, high correlations between market return proxies (TASI, MSCI-SADI and S&P-SADITR) do not cause multicollinearity issues, as each one will be regressed in separate models. Similarly, the high correlation between SMB and $\mathrm{SMB}_{B/M}$ will not be problematic, as these two variables are regressed in different models.

Table 5.1

Summary Statistics of Active Fund Risk Premiums, Passive Fund Risk Premiums, Market Risk Premiums and Risk Factors During the January 2010 – December 2020 period

No.	Variable	*M* %	*SD*%	Autocorrelation for lag			Correlation %										
				1	2	12	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	Active fund risk premium	0.523	4.62	0.11	-0.08	0.09	100										
2	Passive fund risk premium	0.099	5.21	0.11	-0.14	0.04	92.8	100									
3	TASI risk premium	0.201	5.49	0.06	-0.09	0.03	95.9	95.8	100								
4	MSCI-SADI risk premium	0.241	5.51	0.06	-0.06	0.04	94.6	95.0	98.1	100							
5	S&P-SADITR risk premium	0.468	5.60	0.06	-0.11	0.05	95.8	96.4	99.7	98.1	100						
6	SMB	0.215	5.30	0.08	0.07	-0.05	34.5	21.2	24.9	19.4	23.8	100					
7	$SMB_{B/M}$	0.184	5.50	0.07	0.08	-0.08	37.1	24.3	28.0	22.6	26.8	99.1	100				
8	*HML*	0.415	3.60	0.10	0.11	-0.04	6.13	10.9	9.78	10.9	10.2	-33.1	-28.3	100			
9	*RMW*	-0.03	3.69	0.10	-0.03	0.00	-23.9	-16.4	-21.4	-18.0	-20.5	-60.9	-65.9	11.27	100		
10	*CMA*	-0.248	3.39	0.01	-0.09	0.152	6.08	11.76	11.54	12.21	10.70	-12.0	-4.8	34.5	-7.7	100	
11	*MOM*	0.491	3.71	-0.09	0.10	-0.04	-25.0	-28.4	-27.6	-25.5	-28.1	-17.7	-19.7	7.19	20.18	-14.8	100

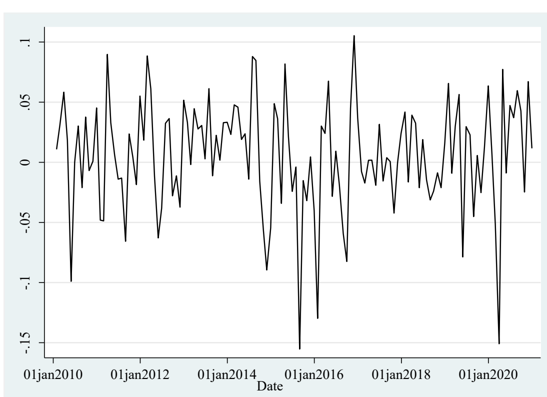
Note. Active fund risk premium is the aggregate active mutual fund returns (equally weighted) minus the risk-free rate of return. Passive fund risk premium is the aggregate passive mutual fund returns (equally weighted) minus the risk-free rate of return. TASI risk premium is the TASI return minus the risk-free rate of return; and MSCI-SADI risk premium is the MSCI-SADI return minus the risk-free rate of return; S&P-SADITR risk premium is the S&P-SADITR return minus the risk-free rate of return. *SMB* is the systematic size risk factor that is based on the FF5FM as in Equation (7), $SMB_{B/M}$ is the systematic size risk factor that is based on the FF3FM, *HML* is the systematic value risk factor, *RMW* is the systematic profitability risk factor, *CMA* is the systematic investment risk factor and *MOM* is the systematic momentum risk factor.

Figure 5.1 provides a visual representation of the time-series return fluctuations for both active and passive fund risk premiums, as well as other risk factors. Plots 1 and 2 show that the active fund risk premium fluctuated between −15.5% and 10.5%, while the passive fund risk premium fluctuated between −16.8% and 15.2%.

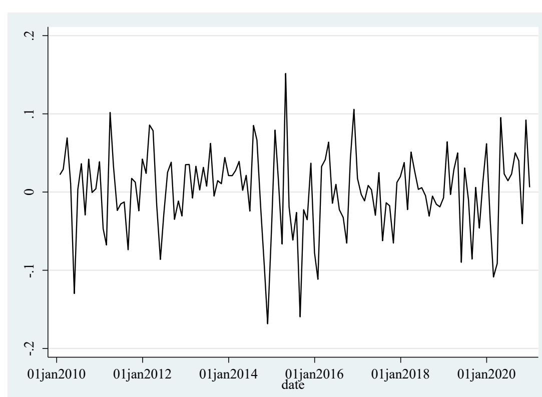
Plots 3–11 present the time-series fluctuations for the TASI risk premium, MSCI-SADI risk premium, S&P-SADITR risk premium, SMB, $SMB_{\mathrm{B/M}}$, HML, RMW, CMA and MOM, respectively. The returns of the risk factors varied considerably, which may better explain the variations in mutual fund returns. Among these factors, the risk premiums of TASI, MSCI-SADI and S&P-SADITR had the highest return variations during the overall sample period. The subsequent sections present details regarding the hypothesis testing and fulfilling the research objectives.

Figure 5.1

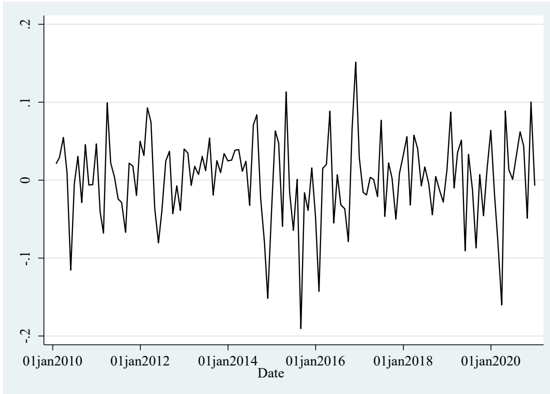
Monthly Return Fluctuations for Market Risk Premiums (TASI, MSCI-SADI, S&P-SADITR) and the Risk Factors of Size (SMB), Value (HML), Profitability (RMW), Investment (CMA) and Momentum (MOM) in the Saudi Market: January 2010 – December 2020



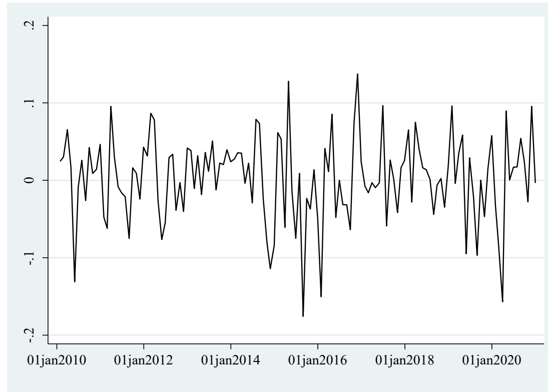
Plot 1: Active fund risk premium



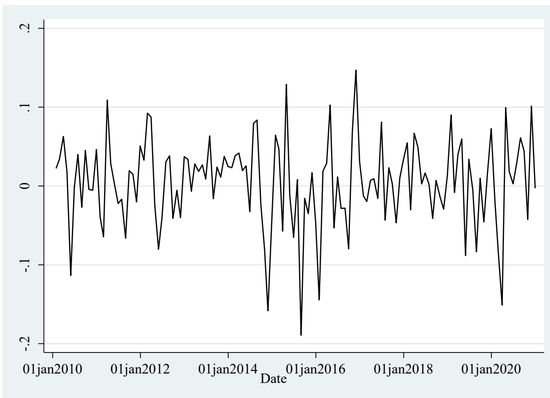
Plot 2: Passive fund risk premium



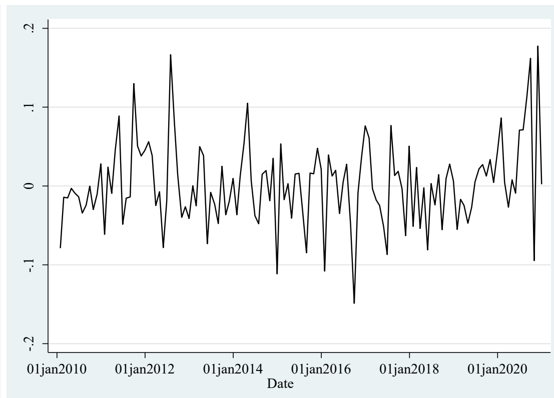
Plot 3: TASI risk premiums



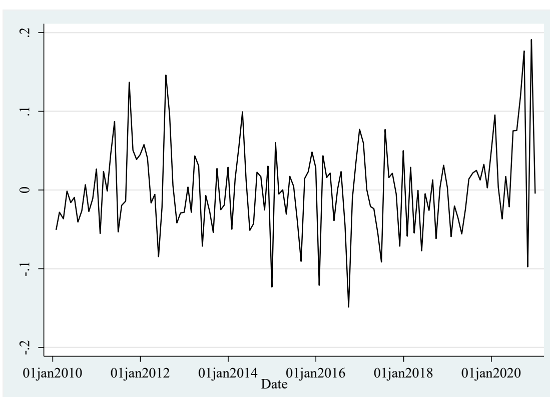
Plot 4: MSCI-SADI risk premiums



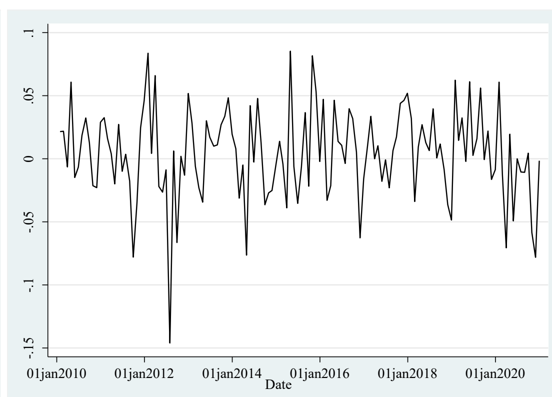
Plot 5: S&P-SADITR risk premiums



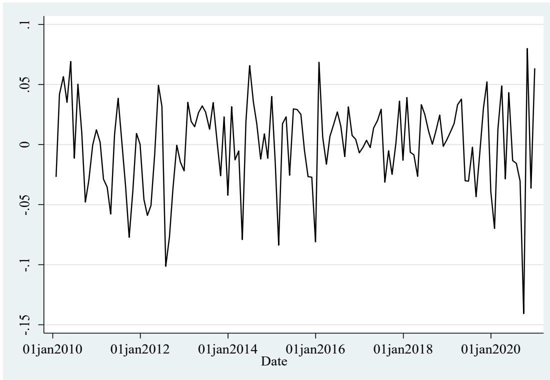
Plot 6: SMB



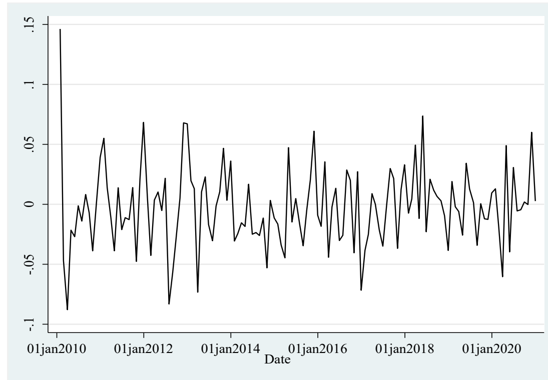
Plot 7: $SMB_{B/M}$



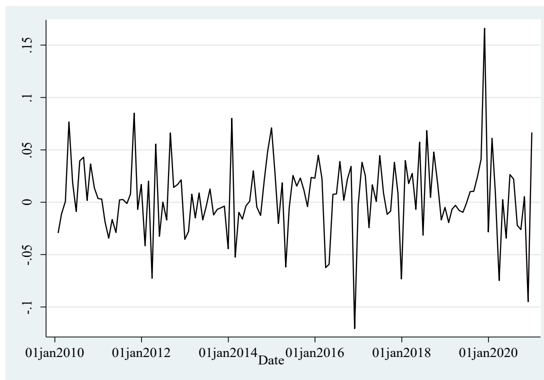
Plot 8: *HML*



Plot 9: *RMW*



Plot 10: *CMA*



Plot 11: *MOM*

Note. The researcher calculated all factors as explained in Chapter 4 and used the Stata software to generate the figure. *SMB*, *HML*, *RMW*, *CMA* and *MOM* stand for the systematic risk factors of size (small minus big), value (high minus low), profitability (robust minus weak), investment (conservative minus aggressive) and momentum (winner minus loser), respectively.

5.3 Efficiency of Models That Measure Mutual Fund Performance

The study of mutual fund performance is significantly influenced by the development of asset pricing models, as they play a crucial role in evaluating the risk-adjusted returns of mutual funds. Active mutual funds inherently carry unique investment styles, which introduces additional risks. Failure to consider these risks in asset pricing models can result in an overestimation of a mutual fund's risk-adjusted return performance, which is commonly known as alpha.[25]

[25] It is also known as unexplained returns and abnormal returns.

Conversely, incorporating risk factors that better capture the drivers of fund returns can minimise the risk-adjusted return performance (unexplained returns), bringing the alpha closer to zero.

The employment of asset pricing models to assess active mutual fund performance traces back to Jensen (1968), who derived Jensen's alpha within the framework of the CAPM. However, challenges to its validity prompted Fama and French (1993) to enhance the CAPM by introducing two additional risk factors: size and value. Building upon their work, Carhart (1997) incorporated momentum as a fourth factor. These advancements led to the widespread application of the FF3FM and the FFC4FM for estimating mutual funds' risk-adjusted performance.

More recent advancements in the field have produced the FF5FM and the FFC6FM, which demonstrate superior performance in explaining the intricate relationship between returns and risks (Fama & French, 2015, 2018). Despite these strides, the integration of these advanced asset pricing models into studies estimating mutual fund performance has been limited. Only a handful of studies have applied the FF5FM to assess risk-adjusted performance in developed markets (e.g. Mustafa & Ali, 2016), underscoring the need for further exploration. Moreover, we did not find a published study that has applied the FF5FM or the FFC6FM to estimate mutual fund performance in Saudi Arabia. Prior studies applied the SFM, the FF3FM and the FFC4FM, arbitrarily assuming that these models are efficient in explaining mutual fund returns (Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Merdad et al., 2016).

Hence, this study aims to assess the efficiency of five competing asset pricing models in explaining mutual fund returns: the SFM, with only the market risk factor; the FF3FM, incorporating market, size and value risk factors; the FF5FM, with the market, size, value, profitability and investment risk factors; the FFC4FM, comprising market, size, value and momentum risk factors; and the FFC6FM, encompassing the market, size, value, profitability, investment and momentum risk factors. To achieve this objective, the study employs the GRS F-test statistic, GRS J-test statistic and MAA.

The GRS test, developed by Gibbons et al. (1989), was initially designed to examine whether intercepts from multiple regression models are jointly zero. However, in financial studies, GRS tests and MAA are employed to rank asset pricing models according to their efficiency in explaining portfolio returns (Kamstra & Shi, 2021). In line with this approach, this study evaluates the efficiency of the selected models across a broad spectrum of portfolios composed of mutual fund returns. To construct these portfolios, it follows the approach outlined by Huij and Verbeek (2009), creating quantile portfolios based on mutual funds' investment styles. The study estimates individual fund sensitivity to risk factors—market, size, value, profitability, investment and momentum—as defined in Equation (8). Subsequently, funds are classified into three quantiles by their sensitivity to each risk factor: low, medium and high. This process results in the construction of nine portfolios (low–low, low–medium, low–high, medium–low, medium–medium, medium–high, high–low, high–medium and high–high) for each of the 15 cross-sections between factors, totalling 135 portfolios (whose average returns are presented in Table 5.2). The GRS F-test and GRS J-test both penalise models that include additional explanatory variables with insufficient explanatory power. Holding other factors constant, a higher unexplained variation in the dependent variable and a greater number of explanatory factors increase the value of GRS F-test and GRS J-test statistics. Consequently, the model resulting in the smallest GRS test statistics, which indicates superior explanatory power for portfolio returns, is favoured (Kamstra & Shi, 2021). In addition, a model generating the smallest MAA, which suggests lower unexplained returns on average, is favoured.

Table 5.2

Summary Statistics of Average Returns (%) for 135 Portfolios Constructed Based on Risk Factors: January 2010 – December 2020

	Panel A: Market–*SMB*				Panel F: *SMB–HML*				Panel K: *HML–CMA*		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Low	0.30068	0.3037	0.69845	Low	0.65336	0.35109	0.58375	Low	0.47786	0.84936	0.48392
Medium	0.49302	0.55889	0.55053	Medium	0.31768	0.5093	0.42863	Medium	0.44162	0.52335	0.41597
High	0.5753	0.51984	0.38993	High	0.61184	0.45812	0.52665	High	0.08297	0.55524	0.54892
	Panel B: *Market–HML*				Panel G: *SMB–RMW*				Panel L: *HML–MOM*		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Low	0.56175	0.29068	0.50964	Low	0.60968	0.58426	0.43742	Low	0.30179	0.86796	0.72551
Medium	0.5446	0.50121	0.55213	Medium	0.56416	0.42328	0.53991	Medium	0.46126	0.56808	0.2735
High	0.4893	0.48342	0.51017	High	0.50329	0.33808	0.27461	High	0.39121	0.50999	0.60009
	Panel C: Market–*RMW*				Panel H: SMB-CMA				Panel M: RMW-CMA		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Low	0.70245	0.19498	0.47421	Low	0.37725	0.53914	0.46929	Low	0.28113	0.57363	0.53394
Medium	0.64352	0.46646	0.51615	Medium	0.43729	0.50544	0.39045	Medium	0.3204	0.54929	0.31696
High	0.47553	0.57253	0.3893	High	0.28696	0.60203	0.4261	High	0.45117	0.27242	0.44833
	Panel D: Market–*CMA*				Panel I: SMB-MOM				Panel N: RMW-MOM		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Low	0.25426	0.60579	0.50796	Low	0.53888	0.54556	0.5126	Low	0.44027	0.44693	0.65486
Medium	0.36709	0.54465	0.486	Medium	0.35079	0.57587	0.22505	Medium	0.36492	0.5536	0.39282
High	0.50723	0.52665	0.38617	High	0.38076	0.44918	0.7531	High	0.19996	0.5157	0.49307
	Panel E: Market–*MOM*				Panel J: HML-RMW				Panel O: CMA-MOM		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Low	0.17541	0.69926	0.23588	Low	0.61432	0.64542	0.52452	Low	0.35728	0.48314	0.19503
Medium	0.43075	0.46924	0.61015	Medium	0.52961	0.41353	0.49172	Medium	0.51857	0.60258	0.41671
High	0.41793	0.59591	0.48536	High	0.5791	0.54555	0.43591	High	0.27726	0.35912	0.81983

Note. This table presents the equally-weighted returns for the 135 portfolios. Portfolios are classified according to their sensitivity to each risk factor into three quantiles: low, medium and high. Then, nine portfolios are constructed (low–low, low–medium, low–high, medium–low, medium–medium, medium–high, high–low, high–medium and high–high) for each of the 15 cross-sections between factors (market–size, market–value, market–profitability, market–investment, market–momentum, size–value, size–profitability, size–investment, size–momentum, value–profitability, value–investment, value–momentum, profitability–investment, profitability–momentum and investment–momentum).

Table 5.3 presents the average results of the GRS F-test statistic, GRS J-test statistic and MAA for the SFM, FF3FM, FF5FM, FFC4FM and FFC6FM across the 135 portfolios.[26] Columns 2–4 identify the market risk factor as TASI, Columns 5–7 use MSCI-SADI, and Columns 8–10 employ S&P-SADITR. Turning to hypothesis testing, Hypothesis 1.A tests whether multi-factor pricing models explain the expected return of active mutual funds better than the SFM. The comparison reveals that multi-factor models consistently outperform SFM in explaining mutual fund returns across the 15 sets of portfolios. For TASI as the market risk factor (Columns 2–4), SFM produces the highest average GRS F-test statistics of 2.85, GRS J-test statistics of 27.57 and MAA of 0.32%. Similarly, when using MSCI-SADI (Columns 5–7) and S&P-SADITR (Columns 8–10) as the market risk factors, multi-factor models still consistently yield lower GRS F-test statistics, GRS J-test statistics and MAA than the SFM. Smaller GRS test statistics and MAA are favoured, indicating better explanatory power and less unexplained returns. Smaller MAA is also favoured as it means less unexplained returns. Thus, the lower results of GRS F-test and GRS J-test statistics and MAA, the better a model explain funds returns. These findings fail to reject the hypothesis that multi-factor pricing models measure the performance of active mutual funds better than SFM. This aligns with the study hypothesis that multi-factor pricing models provide a superior measure of the performance of active mutual funds in Saudi Arabia, adjusting for the risks undertaken. These findings are in line with that of prior studies that have consistently shown the superior performance of multi-factor models over SFM (Fama & French, 1992, 1993).

Next, Hypothesis 1.B examines whether the FF5FM explains the returns of active mutual funds better than the FF3FM. The findings suggest that, indeed, the FF5FM offers a more comprehensive explanation of mutual fund returns than the FF3FM. To illustrate, when TASI

[26] Detailed results for each set of nine portfolios within the 15 cross-sections can be found in Appendix B.

serves as the market risk factor (Columns 2–4 in Table 5.3), the FF5FM records an F-test statistic of 2.66, J-test statistic of 26.57 and MAA of 0.26%, which are lower than the FF3FM's respective values of 2.85, 27.97 and 0.30%. Similar outcomes are observed when MSCI-SADI (Columns 5–7) and S&P-SADITR (Columns 8–10) are considered market risk factors. In both cases, the FF5FM consistently exhibits lower GRS statistics and MAA than the FF3FM. Lower GRS test statistics are preferred, indicating a better ability to explain portfolio returns (Kamstra & Shi, 2021). Consequently, the results of the GRS F-test and J-test statistics, as well as MAA, fail to reject the hypothesis that the FF5FM provides a better explanation for active mutual fund returns than the FF3FM. These findings suggest that the FF5FM effectively adjusts returns for the risks associated with profitability and investment undertaken by mutual funds. This aligns with existing asset pricing literature that underscores the significance of the relationship between portfolio returns and profitability and investment risk factors (Fama & French, 2015, 2017).

Last, Hypothesis 1.C examines whether the FFC6FM provides a superior explanation for active mutual fund returns compared with the FFC4FM. The FFC4FM has been widely used in the area of mutual fund performance, and Fama and French (2018) recently incorporated the momentum factor into their earlier FF5FM, resulting in the FFC6FM. The results in Table 5.3 show that the FFC6FM consistently produces lower GRS F-test and J-test statistics, and MAA, than the FFC4FM and the FF5FM do, indicating that the FFC6FM offers a more robust explanation of mutual fund returns than the FFC4FM and even the FF5FM. For instance, when considering TASI as the market risk factor (Columns 2–4), the FFC6FM averages an F-test statistic of 2.50, J-test statistic of 25.19 and MAA of 0.26%. These values are lower than those of the FFC4FM (F-test statistic of 2.62, J-test statistic of 25.98 and MAA of 0.29%) and the FF5FM (F-test statistic of 2.66, J-test statistic of 26.58 and MAA of 0.26%). The superiority of the FFC6FM is consistently observed even when using MSCI-SADI (Columns 5–7) and S&P-SADITR (Columns 8–10) as market risk factors. Since GRS test statistics by a model are preferred as it better explains portfolios returns, the findings fail to reject the hypothesis that the FFC6FM better explains the returns of active mutual funds than any other model. The findings suggest that the FFC6FM better adjusts returns for the risks of market, size, value, profitability, investment and momentum taken by mutual funds. The findings of this study support that of past literature on asset pricing that emphasises the relationship between portfolios returns and the risk factors of market, size, value, profitability, investment and momentum (Fama & French, 2018).

Table 5.3

Efficiency Test of SFM, FF3FM, FF5FM, FFC4FM and FFC6FM in Explaining Monthly Active Fund Returns (Analysis Period: January 2010 – December 2020)

Models	TASI benchmark			MSCI-SADI benchmark			S&P-SADITR benchmark		
	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|
SFM	2.853	27.569	0.0032	2.692	26.207	0.0029	1.879	18.160	0.0014
FF3FM	2.846	27.967	0.0030	2.627	25.818	0.0027	1.890	18.580	0.0013
FF5FM	2.663	26.575	0.0026	2.439	24.384	0.0023	1.824	18.231	0.0012
FFC4FM	2.617	25.976	0.0029	2.420	23.989	0.0026	1.782	17.663	0.0012
FFC6FM	2.498	25.189	0.0026	2.295	23.130	0.0023	1.740	17.550	0.0011

Note. The table presents the average results for the GRS F-test statistic, GRS J-test statistic and MAA to examine the efficiency of the SFM, FF3FM, FF5FM, FFC4FM and FFC6FM in explaining monthly mutual fund excess returns. The detailed results of the GRS F-test statistic, GRS J-test statistic and MAA for each set of nine portfolios are reported in Appendix B. TASI, MSCI-SADI and S&P-SADITR were employed as the market factor separately for each set of nine regressions across the SFM, FF3FM, FF5FM, FFC4FM and FFC6FM. The GRS F-test and J-test statistics examine whether the estimated values of the intercepts (alphas) of the nine portfolios are jointly zero; MAA |α| is the average absolute value of the nine intercepts.

In conclusion, the FFC6FM emerges as the most efficient model for explaining mutual fund returns. The incorporation of the Carhart momentum factor into the FF5FM by Fama and French (2018) has enhanced the performance of the FF5FM in explaining portfolio returns. Despite the advancements in the asset pricing literature, the mutual fund literature has been slow to integrate these developments. Past studies often relied on simpler models, such as the SFM, the FF3FM and the FF4FM, assuming that these are efficient in explaining mutual fund returns (Al Rahahleh & Bhatti, 2022; BinMahfouz & Hassan, 2012; Merdad et al., 2016).

This study, which employs the GRS F-test and J-test statistics, and MAA, finds that FFC6FM explains mutual fund returns better, providing more accurate unexplained returns (alpha). The market, size, value, profitability, investment and momentum risk factors collectively provide a more comprehensive explanation for mutual fund returns. These factors effectively minimise unexplained fund returns, underscoring the significance of adjusting mutual fund returns to these factors when measuring risk-adjusted return performance. Consequently, utilising incomplete models that do not account for these risks may lead to an overestimation of mutual fund actual risk-adjusted return performance (alpha). These findings hold direct implications for the subsequent analysis of risk-adjusted return performance in Section 5.4.2.

5.4 Analysis of Mutual Fund Aggregate Performance

The empirical examination of mutual fund performance is crucial in the finance field. Traditional finance theory assumes that all investors, including professional fund managers and individual traders, are perfectly rational and share homogeneous expectations. According to this theory, persistent outperformance of the overall market portfolio by any investor, including fund managers, is not expected (Fama, 1970, 1991; Malkiel, 2020). Empirical evidence aligned with this theory suggests that mutual funds generally cannot consistently outperform the market

(Carhart, 1997; Fama & French, 2010; Malkiel, 1995). In contrast, behavioural finance theory posits the coexistence of rational investors and irrational traders. According to this theory, asset prices may deviate from their intrinsic values, allowing sophisticated investors to outperform the overall market (Shiller, 2003, 2015). Empirical support for this theory has been provided by studies indicating that mutual funds can indeed demonstrate outperformance (Kosowski et al., 2006, 2007; Wermers, 2000).

In the following, this study conducts a comprehensive empirical analysis of mutual fund performance in Saudi Arabia over the overall sample period and during subsample periods focusing on SMEs, as defined in Chapter 4. The analysis encompasses benchmark-adjusted return performance (Section 5.4.1), risk-adjusted return performance (Section 5.4.2) and the market timing of mutual fund performance (Section 5.4.3).

5.4.1 Analysis of Benchmark-Adjusted Return Performance

Through this analysis of benchmark-adjusted return performance, this study examines whether mutual funds have generated significantly higher returns than the market (proxied by returns of the following indices: TASI, MSCI-SADI and S&P-SADI). To this end, the difference between mutual fund unadjusted returns and market unadjusted returns (mean difference) is measured.[27] Subsequently, a one-sample *t*-test is employed to determine the significance of this difference from zero. A positive and significant *t*-test result indicates superior performance, while a negative and significant *t*-test result suggests inferior performance. However, it is essential to note that benchmark-adjusted return performance does not account for the additional risks undertaken by funds to generate returns.

[27] Some studies refer to the benchmark-adjusted performance as the mean difference or difference in means.

This section is divided into the following subsections: Subsections 5.4.1.1.1 and 5.4.1.2.1 address Hypotheses 2.A and 2.D, respectively, which examine the benchmark-adjusted return performance of active funds and passive funds. Subsections 5.4.1.1.2 and 5.4.1.2.2 tackle Hypotheses 2.B and 2.E, respectively, examining the variation in benchmark-adjusted return performance between the overall sample period and subsample periods for active and passive funds. Subsections 5.4.1.1.3 and 5.4.1.2.3 address Hypotheses 2.C and 2.F, respectively, exploring the performance variation for active and passive funds when benchmark-adjusted return performance is measured against different proxies of market returns. Last, Subsection 5.4.1.3 addresses Hypothesis 2.G, investigating whether there are any significant differences between active and passive funds in terms of their benchmark-adjusted return performance.

5.4.1.1 Active Mutual Funds.

5.4.1.1.1 Benchmark-Adjusted Return Performance

Table 5.4 presents the results of the benchmark-adjusted performance for active funds during both the overall sample and SME periods. The table includes the unadjusted returns for active funds (Row 1) and for each index (Rows 2–4), and below the unadjusted returns of each index, it details the benchmark-adjusted return performance (mean difference) between active funds and each respective index.

Hypothesis 2.A examines whether the unadjusted returns of active funds differ significantly from those of the market. The empirical results, as shown in the mean difference and from the one-sample *t*-test for the overall sample period, fail to reject the null hypothesis that the unadjusted returns of active funds significantly surpassed that of the market by 0.257% and 0.218% compared with TASI and MSCI-SADI, respectively. However, there was a non-significant unadjusted return difference against S&P-SADI. Overall, these findings reveal that despite the management costs borne by active funds, their net returns were significantly higher than the market returns.

These results correspond with the findings of Al Rahahleh and Bhatti (2022) who reported a positive and significant 0.410% mean difference against TASI, and contrast with those of BinMahfouz and Hassan (2012), Merdad et al. (2010), Omri et al. (2019) and Zouaoui (2019), who did not find significant differences between active fund unadjusted returns and indices' returns. The alignment of the current results with those of Al Rahahleh and Bhatti (2022) may be attributed to the inclusive analysis of the entire sample of active mutual funds, whereas other studies have often separated the mutual fund sample into Islamic-Sharia compliant and non-Islamic-Sharia compliant funds or used a smaller sample from a single fund provider. However, the current study goes a step further by analysing benchmark-adjusted performance against different proxies of market returns. Notably, it results show that the benchmark-adjusted performance against S&P-SADITR does not correspond with the benchmark-adjusted performance against TASI and MSCI-SADI, primarily because of the consideration of dividend accumulation in S&P-SADITR.

The current findings are also distinguished from those of past studies through an analysis of subsamples. As outlined in Table 5.4, Hypothesis 2.A is not rejected during periods of financial crises and bearish and bullish markets. In the financial crises period, active funds demonstrated significant and higher returns of 0.737%, 0.835% and 0.476% above TASI, MSCI-SADI and S&P-SADI, respectively. This unexpected resilience underscores the ability of active funds to outperform in challenging financial conditions. Further, the analysis reveals contrasting outcomes for mutual fund performance during bullish and bearish market phases. Mutual funds exhibited their most positive benchmark-adjusted return performance during bearish markets, registering significant differences of 1.149%, 1.284% and 1.067% compared with TASI, MSCI-SADI and

S&P-SADITR, respectively. Conversely, during bullish markets, active mutual funds consistently lagged behind TASI, MSCI-SADI and S&P-SADITR, with significant mean differences of −0.420%, −0.617% and −0.778%, respectively. This phenomenon of positive performance during bearish market periods and negative performance during bullish market periods could be explained by mutual funds' strategic commitment to holding cash. In practice, fund managers allocate a portion of assets to cash, imposing a drag on fund performance. However, this cash reserve empowers managers to capitalise on opportunities and meet unexpected redemption demands (Simutin, 2014). Consequently, holding cash during bullish market periods may lead to significant underperformance, given its non-profit-yielding nature in such market conditions. Conversely, holding cash during bearish market periods fosters significant outperformance, as the cash reserve proportionally mitigates losses in a bearish market scenario.

Another important subsample analysis includes the periods prior and after the 2015 financial reforms. On testing Hypothesis 2.A for these periods, the results in Table 5.4 reveal distinct performance of active funds in these two periods. Before the implementation of these reforms, mutual funds exhibited a significant outperformance against TASI, MSCI-SADI and S&P-SADITR, with significant mean differences of 0.490%, 0.506% and 0.260%, respectively. However, this outperformance against all three indices disappeared after the financial reforms were implemented. Consequently, this study fails to reject Hypothesis 2.A for the period before the financial reforms but is rejected for the post-reform period.

To validate the robustness of these results and confirm that the change in active fund benchmark-adjusted performance is attributable to the financial reforms, one-sample *t*-tests and structural break tests are conducted. First, a one-sample *t*-test comparing such performance before and after financial reforms reveals a significant difference. The benchmark-adjusted performance of active funds before financial reforms (0.49%) was significantly higher by 0.26% ($t = 1.6$, p-value = 0.056), than their benchmark-adjusted performance after financial reforms (0.026%). Second, the study applies the Wald (1943) structural break test to identify a structural break after July 2015 (implementation of the financial reforms). The results confirm a significant change in active fund benchmark-adjusted performance after the financial reforms ($\chi^2 = 5.02$, p-value = 0.08).[28]

To confirm that this significant structural change in active fund benchmark-adjusted performance is not a reflection of a significant structural change in the stock market returns before and after financial reforms, the study performs similar tests on equity market unadjusted returns (TASI). The one-sample t-test comparing such returns before and after financial reforms shows a non-significant difference of 0.66621% ($t = 0.696$). In addition, the Wald (1943) test for a structural break in TASI unadjusted returns in July 2015 confirms no significant change in equity market unadjusted returns after the financial reforms ($\chi^2 = 2.26$, p-value = 0.323). This confirms that the observed structural change is specific to active fund benchmark-adjusted performance. Further discussion on potential reasons for the significant difference in active fund performance before and after financial reforms is presented later in this chapter.[29]

[28] These results reflect the benchmark-adjusted performance based on TASI; the analysis based on MSCI-SADI and S&P-SADITR yields similar results.

[29] The discussion is located in Section 5.4.2.1.1, after the findings of risk-adjusted return performance for the periods before and after financial reforms are presented.

Table 5.4

Benchmark-Adjusted Return Performance (Mean Difference) of Active Funds Based on TASI, MSCI-SADI and S&P-SADITR for the Overall Period (January 2010 – December 2020) and Subsample Periods

No.	Unadjusted returns of	Variable	Overall	Financial crises	Bullish market	Bearish market	Before FRs	After FRs
1	Active funds	Mean	0.00523	-0.00928	0.03485	-0.03374	0.01089	-0.00042
2	TASI	Mean	0.00265	-0.01665	0.03905	-0.04524	0.00598	-0.00068
		Mean difference	0.00258**	0.00738**	-0.0042***	0.0115***	0.0049***	0.00026
			t = 1.7606	t = 2.3074	t = -2.4996	t = 5.6104	t = 2.7222	t = 0.1117
3	MSCI-SADI	Mean	0.003048	-0.017634	0.038585	-0.043711	0.005819	0.000277
		Mean difference	0.00218*	0.00836***	-0.00617***	0.01285***	0.00507***	-0.0007
			t = 1.3330	t = 2.6289	t = -3.3012	t = 5.8898	t = 2.6357	t = -0.2669
4	S&P-SADITR	Mean	0.00533	-0.01405	0.04127	-0.04499	0.00828	0.00237
		Mean difference	-0.0001	0.00477*	-0.00779***	0.01068***	0.00261*	-0.0028
			t = -0.0618	t = 1.3605	t = -4.5457	t = 5.1342	t = 1.3728	t = -1.1691

Note. The active mutual funds' unadjusted returns in Row 1 are the base of comparison. Row 2 presents the TASI unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of active mutual funds' unadjusted returns against TASI. Row 3 presents the MSCI-SADI unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of active mutual funds' unadjusted returns against MSCI-SADI. Row 4 presents the S&P-SADITR unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of active mutual funds' unadjusted returns against S&P-SADITR. A one-sample *t*-statistics test is used to test the significant deviation of difference in returns from zero, which is reported below the mean difference. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Before FRs and After FRs stand for the periods before and after the 2015 financial reforms, respectively.

5.4.1.1.2 Performance Variation Between Overall Sample and Subsamples

Building upon results for the benchmark-adjusted performance obtained in the previous section, this section investigates whether there are differences in funds' benchmark-adjusted performance between the subsample periods and the overall sample period. Hypothesis 2.B examines whether active fund benchmark-adjusted performance behaved differently during the subsample period than in the overall sample period. To examine Hypothesis 2.B, the study applies two-sample *t*-tests to identify significant differences between active benchmark-adjusted performance during the overall sample period and each subsample period. A significant positive *t*-statistic indicates better benchmark-adjusted performance during the overall sample period than during a subsample period, while a significant negative *t*-statistic indicates better benchmark-adjusted return performance during subsample periods than during the overall sample period.

Table 5.5 presents the results of these two-sample *t*-tests. The results show that active funds exhibited significantly better benchmark-adjusted performance during financial crises and bearish market periods than during the overall sample period. These results are robust across the three benchmark-adjusted returns measured against TASI, MSCI-SADI and S&P-SADITR, respectively. In contrast, active fund benchmark-adjusted performance during bullish market periods was significantly below their performance during the overall sample period. Therefore, the test fails to reject Hypothesis 2.B, suggesting that active fund benchmark-adjusted performance significantly varies during financial crises and bearish market periods compared with such performance in the overall sample period. These results align with those of Kosowski (2011) as regards the better performance of active funds during market downturns and confirm the value added by active management during unfavourable times. However, Hypothesis 2.B is rejected on comparing the active fund benchmark-adjusted performance during the overall sample period with that during the periods before and after financial reforms.

5.4.1.1.3 Performance Variation Across Benchmark Indices

In contrast to the previous section, which maintains the benchmark-adjusted performance constant across indices and compares it across different sample periods, this section holds the performance constant through sample periods and compares it across different indices. Thus, it investigates potential differences between active fund benchmark-adjusted performance derived from three benchmark indices as proxies for market returns. The pair-comparison includes benchmark-adjusted performance based on TASI – MSCI-SADI, TASI – S&P-SADITR and MSCI-SADI – S&P-SADITR. To examine Hypothesis 2.C, the study employs two-sample *t*-tests to identify any significant differences in the benchmark-adjusted performance across each pair of indices. A significant *t*-statistic suggests a significant difference in such performance computed using two different benchmark indices, indicating a variation in the inference about the benchmark-adjusted performance of active funds when using different market return proxies.

The results in Table 5.6 show that active fund benchmark-adjusted performance based on TASI is significantly higher than that based on S&P-SADITR, during the overall sample period and bullish market periods. Accordingly, the statistical results fail to reject Hypothesis 2.C, suggesting that the inference of benchmark-adjusted performance of active funds varies when using TASI in comparison to S&P-SADITR. These results are consistent with those of studies that observed the effect of selecting a market return proxy on the inference of fund performance (Grinblatt & Titman, 1994). Mutual funds generate significantly higher benchmark-adjusted performance when it is measured using TASI than when it is measured using S&P-SADITR because S&P-SADITR uses a more rigorous method to represent market returns by accumulating constituents' dividends. These results underscore the significant impact of selecting a market return proxy on the inference of active fund benchmark-adjusted performance, emphasising the importance of applying an appropriate benchmark index to proxy market returns for measuring mutual fund performance. However, Hypothesis 2.C is rejected when using TASI in comparison to MSCI-SADI, and MSCI-SADI in comparison to S&P-SADITR.

Table 5.5

Results of Two-Sample t-Tests Comparing Active Fund Performance Between the Overall Sample Period (January 2010 – December 2020) and the Subsample Periods of SMEs

Index	Overall-FC		Overall-Bullish		Overall-Bearish		Overall-Before FRs		Overall-After FRs	
TASI	0.00258	0.00738	0.00258	-0.0042	0.00258	0.0115	0.00258	0.00490	0.00258	0.00026
	t= -1.54*		t = 2.92***		t = -3.43***		t = -0.96		t = 0.88	
MSCI-SADI	0.00218	0.00836	0.00218	-0.00617	0.00218	0.01285	0.00218	0.00507	0.00218	-0.0007
	t = -1.84**		t = 3.22***		t = -3.72***		t = -1.07		t = 0.97	
S&P-SADITR	-0.0001	0.00477	-0.0001	-0.00779	-0.0001	0.01068	-0.0001	0.00261	-0.0001	-0.0028
	t = -1.46*		t = 3.20***		t = -3.94***		t = -1.06		t = 0.98	

Note. The table presents active mutual fund benchmark-adjusted returns (mean difference) for the overall sample period as against each subsample period; below these, it presents the two-sample *t*-test results of benchmark-adjusted returns between the overall sample period and each subsample period. The second column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of financial crisis; the third column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of a bullish market; the fourth column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of a bearish market; the fifth column compares benchmark-adjusted returns during the overall sample period with that of the pre-financial-reform subsample period; and the sixth column compares benchmark-adjusted returns during the overall sample period with that of the post-financial-reform subsample period. The significance of the two-sample *t*-test results is determined through the *t*-student distribution. If the *t*-statistic is more extreme than the critical value in the *t*-student distribution, this test rejects its null hypothesis that the tested values are equal and accepts the alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.6

Results of Two-Sample t-Tests Comparing the Benchmark-Adjusted Return Performance of Active Funds Derived from Three Different Proxies of Market Returns

Fund	Overall sample		Financial crisis		Bullish market		Bearish market		Before financial reforms		After financial reforms	
	TASI	MSCI -SADI	TASI	MSCI-SADI	TASI	MSCI-SADI	TASI	MSCI-SADI	TASI	MSCI -SADI	TASI	MSCI -SADI
MSCI-SADI	t=0.22	--	t=-0.22	--	t=0.78	--	t=-0.45	--	t=-0.06	--	t=0.27	--
S&P-SADITR	t=1.30*	t=1.01	t=0.55	t=0.76	t =1.50*	t=0.64	t=0.28	t=0.72	t=0.88	t=0.91	t=0.92	t=0.59

Note. For each sample period, the two-sample *t*-test was conducted between each pair of indices: TASI – MSCI-SADI, TASI – S&P-SADITR, and MSCI-SADI – S&P-SADITR. The significance of the two-sample *t*-test results is determined through the *t*-student distribution. If the *t*-statistic is more extreme than the critical value in the *t*-student distribution, this test rejects its null hypothesis that the tested values are equal and accepts its alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.1.2 Passive Mutual Funds

5.4.1.2.1 Benchmark-Adjusted Return Performance

Passive mutual funds are renowned for their precise tracking of benchmark indices in developed markets (Buetow & Henderson, 2012). However, some studies have employed benchmark-adjusted return performance to evaluate passive funds (Blitz et al., 2012; Elton et al., 2002, 2019b; Harper et al., 2006). Notably, there has been no prior investigation into the benchmark-adjusted return performance of passive funds in the Saudi market. This study not only addresses this gap but also facilitates an extension of the literature by comparing it with that of active funds, as measured in the preceding section. Hypothesis 2.D has been developed to examine passive fund benchmark-adjusted performance.

The results in Table 5.7 demonstrate that there is no significant difference between the unadjusted returns of passive funds and those of TASI and MSCI-SADI. This difference tends to be negative owing to management fees; however, *t*-tests indicate that this difference is not significantly different from zero, except during bullish and bearish market periods. Accordingly, Hypothesis 2.D is rejected for the overall sample period, periods of financial crises and the periods before and after the financial reforms, but not for bullish and bearish market periods.

In bullish market periods, passive fund unadjusted returns underperformed TASI and MSCI-SADI by −0.442% and −0.526%, respectively. Conversely, during bearish market periods, they outperformed TASI and MSCI-SADI by 0.345% and 0.349%, respectively. Passive funds are not expected to outperform or underperform the market consistently. However, their monthly return performance can vary owing to factors such as their management fees, cash holdings, dividends, inflows and outflows, and replication strategy (Charupat & Miu, 2013). The underperformance during bullish market periods and the outperformance during bearish ones could be attributed to their cash holdings, received dividends and cash flow. For instance, in normal times, passive funds maintain a small amount of cash or semi-cash for potential redemptions. In addition, funds may experience high inflows from new subscribers or receive cash dividends from their portfolios. Holding cash or delaying the reinvestment of cash during bullish market periods causes significant underperformance, as cash does not yield any profit in a bullish market. Conversely, holding cash or delaying reinvestment during bearish market periods leads to significant outperformance, as holding cash proportionally reduces losses in a bearish market.

Furthermore, the results in Table 5.7 indicate that passive funds' unadjusted returns underperformed S&P-SADITR. The returns of S&P-SADITR differ from those of TASI and MSCI-SADI, as S&P-SADITR accounts for accumulated dividends from its constituents in its returns. The *t*-test results show that passive mutual funds significantly underperformed the unadjusted returns of S&P-SADITR by −0.369% during the overall sample period and by −0.751% during bullish market periods. Therefore, this study fails to reject Hypothesis 2.D for the overall sample period, the bullish market period and the periods before and after the financial reforms, when using S&P-SADITR as a proxy for market returns. Further discussion will be presented in the following section on the performance variation across benchmark indices.

Table 5.7

Benchmark-Adjusted Return Performance (Mean Difference) of Passive Funds Based on TASI, MSCI-SADI and S&P-SADITR` for the Overall Period (January 2010 – December 2020) and Subsample Periods

No.	Unadjusted returns of	Variable	Overall	Financial crises	Bullish market	Bearish market	Before FRs	After FRs
1	Passive fund	Mean	0.00163	-0.01403	0.03463	-0.04178	0.00588	-0.00261
2	TASI	Mean	0.00265	-0.01665	0.03905	-0.04524	0.00599	-0.00068
		Mean difference	-0.00102 t = -0.744	0.00262 t = 0.884	-0.00442** t = -2.579	0.00345* t = 1.640	-0.00011 t = -0.078	-0.00193 t = -0.811
3	MSCI-SADI	Mean	0.00305	-0.01763	0.03859	-0.04371	0.00582	0.00028
		Mean difference	-0.00141 t = -0.947	0.00360 t = 1.136	-0.00526*** t = -2.832	0.00349* t = 1.524	0.00006 t = 0.037	-0.00289 t = -1.132
4	S&P-SADITR	Mean	0.00533	-0.01405	0.04127	-0.04499	0.00828	0.00237
		Mean difference	-0.00369*** t = -2.852	0.00001 t = 0.004	-0.00751*** t = -4.825	0.00165 t = 0.818	-0.00240** t = -2.134	-0.00498** t = -2.137

Note. The passive mutual funds' unadjusted returns in Row 1 are the base of comparison. Row 2 presents the TASI unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of passive mutual funds' unadjusted returns against TASI. Row 3 presents the MSCI-SADI unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of passive mutual funds' unadjusted returns against MSCI-SADI. Row 4 presents the S&P-SADITR unadjusted returns (mean) and below it, the benchmark-adjusted return performance (mean difference) of passive mutual funds' unadjusted returns against S&P-SADITR. A one-sample *t*-statistics test is used to test the significant deviation of difference in returns from zero, which is reported below the mean difference. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Before FRs and After FRs stand for the periods before and after the 2015 financial reforms, respectively.

5.4.1.2.2 Performance Variation Between Overall Sample and Subsample Periods

This section examines whether there are any potential differences in the benchmark-adjusted performance of funds during subsample periods compared with the overall sample period. Hypothesis 2.E investigates the extent to which significant variations in such performance occur during SMEs compared with the overall sample results. The objective of this analysis is to gain insights into the behaviour of passive mutual fund performance amidst SMEs. Table 5.8 presents the results of two-sample *t*-tests, comparing benchmark-adjusted performance during the overall sample period to that in subsample periods. A significantly positive *t*-statistic suggests that this performance was superior during the overall sample period, while a significantly negative *t*-statistic indicates better performance during the subsample periods than the overall period.

Similarly to active funds, passive funds exhibit significantly superior benchmark-adjusted performance during financial crises and bearish market periods compared with the overall period. This observation holds true even when this performance is assessed using different indices, such as TASI, MSCI-SADI and S&P-SADITR, reinforcing the robustness of the conclusion. Conversely, this performance is significantly lower during bullish market periods than during the overall sample period. The statistical results in Table 5.8 fail to reject Hypothesis 2.E, indicating that passive funds deliver significantly better benchmark-adjusted returns during financial crises and bearish market periods, and significantly inferior benchmark-adjusted returns during bullish market periods, compared with normal times. These findings shed light on a unique behaviour exhibited by Saudi Arabian passive funds, aligning with the results of Angelini (2013), who observed higher tracking errors of Italian passive funds during financial crisis periods. Conversely, the result rejects Hypothesis 2.E, suggesting that passive fund benchmark-adjusted return performance does not significantly vary during the periods before and after financial reforms compared with the overall sample period. This insight adds further depth to the understanding about the dynamics within Saudi Arabian passive funds.

5.4.1.2.3 Performance Variation Across Benchmark Indices

In contrast to the previous section, which shows that benchmark-adjusted performance remains constant across indices and compares it across subsample periods, this section maintains a constant benchmark-adjusted performance throughout the sample periods and investigates potential differences between performance derived from three different indices. The pair-comparison includes benchmark-adjusted performance that is based on two different indices as follows: TASI – MSCI-SADI, TASI – S&P-SADITR, and MSCI-SADI – S&P-SADITR. To test Hypothesis 2.F, the study employs two-sample *t*-tests on each pair of indices to identify significant differences in performance across each pair. A significant *t*-statistic indicates a considerable difference between benchmark-adjusted performance calculated using these two different benchmark indices, suggesting a variation in the inference of such performance for passive funds when different market return proxies are used.

The results in Table 5.9 show that the benchmark-adjusted performance measured based on TASI is significantly higher than the mean of such performance measured based on S&P-SADITR during the overall sample period ($t = 1.42$), bullish market periods ($t = 1.34$) and before financial reforms ($t = 1.30$). In addition, the benchmark-adjusted performance measured based on MSCI-SADI is significantly higher than that measured based on S&P-SADITR during the period before financial reforms ($t = 1.28$). Therefore, the statistical tests fail to reject Hypothesis 2.F, indicating that the inference of benchmark-adjusted performance for passive funds varies when using TASI in comparison to S&P-SADITR. However, Hypothesis 2.F is rejected when using TASI in comparison to MSCI-SADI, and MSCI-SADI in comparison to S&P-SADITR. These results underscore the significant impact of selecting a market return proxy on the inference of passive fund benchmark-adjusted performance and highlights the importance of applying an appropriate benchmark index to proxy market returns for measuring mutual fund performance.

Table 5.8

Results of Two-Sample t-Tests Comparing Passive Fund Performance Between the Overall Sample Period (January 2010 – December 2020) and Subsample Periods of SMEs

Index	Overall-FC		Overall-Bullish		Overall-Bearish		Overall-Before		Overall-After	
TASI	-0.00102	0.00262	-0.00102	-0.00442	-0.00102	0.00345	-0.00102	-0.00011	-0.00102	-0.00193
	t = -1.250*		t = 1.525*		t = -1.788**		t = -0.421		t = 0.355	
MSCI-SADI	-0.00141	0.0036	-0.00141	-0.00526	-0.00141	0.00349	-0.00141	0.00006	-0.00141	-0.00289
	t = -1.591*		t = 1.583*		t = -1.807**		t = -0.619		t = 0.531	
S&P-SADITR	-0.00369	0.00001	-0.00369	-0.00751	-0.00369	0.00165	-0.00369	-0.00240	-0.00369	-0.00498
	t = -1.347*		t = 1.844**		t = -2.235**		t = -0.646		t = 0.524	

Note. The table presents passive mutual fund benchmark-adjusted returns (mean difference) for the overall sample period as against each subsample period; below these, it presents the two-sample *t*-test results of benchmark-adjusted returns between the overall sample period and each subsample period. The second column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of financial crisis; the third column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of a bullish market; the fourth column compares benchmark-adjusted returns during the overall sample period with that of the subsample period of a bearish market; the fifth column compares benchmark-adjusted returns during the overall sample period with that of the pre-financial-reform subsample period; and the sixth column compares benchmark-adjusted returns during the overall sample period with that of the post-financial-reform subsample period. The significance of the two-sample *t*-test results is determined through the *t*-student distribution. If the *t*-statistic is more extreme than the critical value in the *t*-student distribution, this test rejects its null hypothesis that the tested values are equal and accepts the alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.9

Results of Two-Sample t-Tests Comparing the Benchmark-Adjusted Return Performance of Passive Funds Derived From Three Different Proxies of Market Returns

	Overall sample		Financial crisis		Bullish market		Bearish market		Before financial reforms		After financial reforms	
	TASI	MSCI-SADI	TASI	MSCI-SADI	TASI	MSCI SADI	TASI	MSCI-SADI	TASI	MSCI-SADI	TASI	MSCI-SADI
MSCI-SADI	t=0.19	--	t=-0.23	--	t=0.33	--	t=-0.01	--	t=-0.08	--	t=0.27	--
S&P-SADITR	t=1.42*	t=1.15	t=0.64	t=0.85	t=1.34*	t=0.93	t=0.62	t=0.60	t=1.30*	t=1.28*	t=0.92	t=0.60

Note. For each sample period, the two-sample *t*-test was conducted between each pair of indices: TASI – MSCI-SADI, TASI – S&P-SADITR, and MSCI-SADI – S&P-SADITR. The significance of the two-sample *t*-test results is determined through the *t*-student distribution. If the *t*-statistic is more extreme than the critical value in the *t*-student distribution, this test rejects its null hypothesis that the tested values are equal and accepts its alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.1.3 Comparison Between Active and Passive Funds

In the preceding sections, the study examined and analysed the benchmark-adjusted performance of active and passive funds separately. However, this section compares the benchmark-adjusted performance of active funds to that of passive funds. According to Frino and Gallagher (2001), given that indices are non-investable instruments and cost-free, these essentially function as paper portfolios. Therefore, this study benchmarks active fund returns against passive fund returns to examine Hypothesis 2.G. It examines whether the active management strategy significantly outperforms the passive management strategy using actual investable passive vehicles. Thus, active funds represent active management and passive funds represent passive management. To the best of this researcher's knowledge, no previous study has provided empirical evidence of the benchmark-adjusted performance of active funds compared with that of passive funds in the Saudi market.

Table 5.10 summarises the benchmark-adjusted return performance of active funds and of passive funds (alphas), which have already been presented in Tables 5.4 and 5.7, respectively. It also presents the results of two-sample *t*-tests to determine whether the former's performance differs significantly from that of the latter. The test results show that active mutual funds exhibited mixed performance against passive mutual funds. Most importantly, during the overall sample period, the former outperformed the latter with a significant and positive returns of 0.359%. These empirical results provide evidence of the superiority of an active management strategy over a passive management strategy in the Saudi market. Furthermore, active funds outperformed passive funds with a significant difference in returns of 0.804% and 0.5% during bearish market periods and before the financial reforms, respectively. Accordingly, the statistical results fail to reject Hypothesis 2.G for the overall period, bearish market periods and the pre-reform period.

Conversely, during financial crises, bullish market periods and the period after the financial reforms, active mutual funds did not record a significant outperformance against passive funds owing to the strong performance of the latter during financial crises and the weak performance of active funds during bullish market periods. Thus, Hypothesis 2.G is rejected for the periods of financial crises, bullish markets and post financial reforms. These results remain robust across the other two indices, MSCI-SADI and S&P-SADITR.

Table 5.10

Results of Two-Sample t-Tests Comparing Benchmark-Adjusted Return Performance of Active Funds and Passive Funds in the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Period	TASI		MSCI-SADI		S&P-SADITR	
	Performance	Difference	Performance	Difference	Performance	Difference
Overall sample period						
Active funds	0.00258**	0.0036**	0.00218*	0.0036*	-0.0001	0.0036**
Passive funds	-0.00102	t = 1.794	-0.00141	t = 1.623	-0.003692***	t = 1.7888
Financial crisis periods						
Active funds	0.00738**	0.00476	0.00836***	0.00476	0.00477*	0.00476
Passive funds	0.00262	t = 1.0916	0.00360	t = 1.060	0.000013	t = 1.061
Bullish market periods						
Active funds	-0.00420***	0.00022	-0.00617***	-0.00091	-0.00779***	-0.00028
Passive funds	-0.00442**	t = 0.090	-0.00526***	t = -0.346	-0.00751***	t = -0.120
Bearish market periods						
Active funds	-0.00420***	0.00805***	-0.00617***	0.00935***	-0.00778***	0.00902***
Passive funds	0.00345*	t = 2.738	0.00349*	t = 2.956	0.00165	t = 3.113
Before financial reforms						
Active funds	0.00490***	0.00501**	0.00507***	0.00501**	0.00261*	0.00501**
Passive funds	-0.00011	t = 2.215	0.0000587	t = 2.026	-0.00240**	t = 2.269
After financial reforms						
Active funds	0.00026	0.00219	-0.0007	0.00219	-0.0028	0.00219
Passive funds	-0.00193	t = 0.662	-0.00289	t = 0.598	-0.00498**	t = 0.655

Note. Performance represents benchmark-adjusted return performance for active and for passive funds, as already presented in Tables 5.4 and 5.7, respectively. Difference is the result of the two-sample *t*-test that examines whether the mean of active fund benchmark-adjusted performance differs significantly from that of passive fund benchmark-adjusted performance. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.2 Risk-Adjusted Return Performance Analysis

To estimate the risk-adjusted return performance of active funds, this study incorporates additional risk factors that mutual funds were exposed to in generating returns. Leveraging multi-factor pricing models identified for efficiency in explaining mutual fund returns in Section 5.3, the FFC6FM is applied to estimate the risk-adjusted return performance of active funds, while the SFM is used to estimate that of passive funds because of their investment style. First, the study forms fund returns into time-series returns by grouping fund returns into equally weighted portfolios, and then subtracts risk-free rate of returns, as detailed in Subsection 4.2.2.2.3. Subsequently, the risk premiums of market proxies (TASI, MSCI-SADI and S&P-SADITR) are set, and the risk factors (*SMB*, *HML*, *RMW*, *CMA* and *MOM*) are structured (as already detailed in Subsections 4.2.2.2.1 and 4.2.2.2.2). Following model estimation, the constant of the model (alpha) is calculated as the average of unexplained variations, with a negative and significant alpha suggesting that mutual funds collectively underperform the market, and a positive and significant alpha implying outperformance, indicating added value for subscribers. This outperformance may stem from either stock selectivity skills or market timing skills.

Dedicating Subsections 5.4.2.1.1 and 5.4.2.2.1 to Hypotheses 2.H and 2.K, respectively, the study investigates the risk-adjusted return performance of active and passive funds. In Subsections 5.4.2.1.2 and 5.4.2.2.2, the study examines Hypotheses 2.I and 2.L, respectively, exploring potential variations in risk-adjusted return performance between the overall sample period and subsample periods for active funds and passive funds. In addition, Subsections 5.4.2.1.3 and 5.4.2.2.3 test Hypotheses 2.G and 2.M, respectively, investigating performance variations for active and passive funds when estimating risk-adjusted performance against different proxies of market returns. Last, Subsection 5.4.2.3 addresses Hypothesis 2.N, examining the potential significant difference in risk-adjusted return performance between active and passive funds.[30]

5.4.2.1 Active Mutual Fund

5.4.2.1.1 Risk-Adjusted Return Performance

In applying the FFC6FM, the study regresses active mutual fund risk premiums[31] on market risk premiums and other risk factors. Table 5.11 presents the model estimations across three panels—Panel A for TASI-RP, Panel B for MSCI-SADI-RP and Panel C for S&P-SADITR-RP—representing market risk premiums (market excess returns). The analysis results show that the FFC6FM demonstrates a remarkable ability to explain high variations in active fund returns. To illustrate, the R-squared results indicate that the model accounts for 80% to 94.4% of active fund return variations across the overall sample and subsample periods when TASI is applied as the market proxy, 80.8% to 94.4% when MSCI-SADI is used and 81.5% to 94.5% when S&P-SADITR is employed. This finding suggests that the three benchmark indices and other risk factors collectively explain substantial levels of active fund return variations. The F-statistics across all regression models indicate statistical significance. To assess multicollinearity, the mean VIF is monitored. Statisticians recommend that a VIF of 5 and less than 10 should cause concern and a VIF of 10 and above should cause a serious concern of multicollinearity (Craney & Surles, 2002; Kennedy, 2008, p. 199; Kutner et al., 2005, p. 409; Menard, 2002, p. 76). In the present study's models, the mean VIFs range within the relatively low levels of 1.38 and 1.72, alleviating concerns of multicollinearity. Individual factor VIFs, detailed in Appendix C, also do not raise concerns regarding potential multicollinearity issues.

[30] All hypotheses were introduced in Chapter 3.

[31] Active mutual fund returns minus one-month free-risk rate of returns.

Next, before proceeding into hypothesis testing, the results in Table 5.11 are discussed. These results shed light on mutual fund behaviour towards risk sensitivity over the overall sample period and during SMEs. Notably, except for market and size risk factors, other risk factors are not significant across the mutual funds. This result is as expected because grouping mutual fund returns into equally weighted portfolios diversifies away individual fund-specific risks. Nevertheless, mutual funds share similar directions of sensitivity to the market factor and size risk factor. The significant sensitivity remains robust across subsample periods. During the overall sample period, all market betas are significant and positive across the three benchmark indices. Market betas, being less than 1, indicate that active mutual funds are less volatile than market portfolios. This trend persists across all subsample periods. When mutual funds increase their exposure to market risk, they tend to outperform the market. For instance, during the period before financial reforms, they recorded the highest market betas (85.6%, 83.6% and 80.1%) coupled with the highest alphas of 0.6%, 0.63% and 0.43%, respectively.[32] Moreover, mutual funds exhibited an investment style favouring profitability risk during the period before financial reforms, contributing to the increase in their risk-adjusted return performance. Furthermore, mutual fund managers tend to decrease exposure to the market portfolio and increase exposure to the size factor (i.e. increase holdings in small firms in a higher proportion relative to their weight in the market) during unfavourable times, such as bearish market periods and financial crises. For instance, in Panel A, sensitivity to the size risk factor increased up to 15.4% and 19.5% during financial crisis periods and bearish market periods.

The study provides evidence that active mutual funds significantly outperformed the market. Table 5.11, Panel A, illustrates that active mutual funds surpassed the market (TASI) with

[32] Against TASI, MSCI-SADI and S&P-SADITR.

monthly significant returns of 0.24% during the overall sample period and a significant monthly return of 0.60% for the period preceding the financial reforms. However, there is insufficient evidence to support their significant outperformance or underperformance during other subsample periods. Similar results are observed when MSCI-SADI is used as the market return proxy in Table 5.11, Panel B. Here, active mutual funds exhibited significant monthly outperformance of 0.207% during the overall sample period and a substantial 0.63% for the period before financial reforms. Accordingly, the results fail to reject the null Hypothesis 2.H that active funds generated positive and significant alpha during the overall period and before financial reforms, while it is rejected for other subsample periods.

These findings confirm the ability of active mutual fund managers to outperform the market over the long term. The current results correspond with those of studies conducted in developed markets (Avramov et al., 2011; Avramov & Wermers, 2006; Berk & Van Binsbergen, 2015; Petajisto, 2013; Wermers, 2000) and those specific to the Saudi market (Al Rahahleh & Bhatti, 2022; Omri et al., 2019). However, studies on the Saudi market often focused on small samples from specific providers or Islamic and non-Islamic law compliant funds, utilising models such as the SFM, FF3FM or FFC4FM to estimate risk-adjusted performance. This study significantly extends both the study period and the sample of funds, encompassing all locally invested mutual funds that have ever existed to account for survival bias. Moreover, the estimation of performance in this study is likely more precise, as it is likely the first to apply the FFC6FM, which considers additional risk factors. The study's empirical evidence challenges some assumptions of the EMH. In a perfectly efficient market, the alpha of mutual funds should not be positive and significant. However, the study reveals a positive and significant alpha, suggesting the potential presence of equity mispricing in the Saudi Arabian equity market. These results could stem from previous evidence reporting asset pricing inefficiencies (weak-form) in the Saudi Arabian equity market (Al-Ajmi & Kim, 2012; Budd, 2012; Butler & Malaikah, 1992; Syed & Bajwa, 2018). In addition, the evidence implies that active mutual fund management can add value, underscoring the potential benefits of this approach.

In Panel C of Table 5.11, the results reject the null Hypothesis 2.H, indicating that active mutual funds cannot outperform S&P-SADITR, except for the period before financial reforms when mutual funds exhibited significant outperformance of 0.43%. As detailed in Chapter 4, S&P-SADITR accumulates higher returns than TASI and MSCI-SADI by incorporating cash dividends from its constituents into the price returns. To the best of this researcher's knowledge, this study is the first to utilise such an index to assess mutual fund performance. The findings show that there is insufficient evidence to support the significant outperformance of active mutual funds when employing an index that includes constituents' cash dividends in the index price returns. This finding contradicts the earlier results based on TASI and MSCI-SADI. Since there is no formal standard for selecting a benchmark index to study mutual fund risk-adjusted performance, these conflicting results may explain the divergent conclusions of prior empirical studies, even those on developed markets. However, the direct pair-comparison of mutual fund risk-adjusted performance based on different indices in the next section will further illuminate this issue. During the period before financial reforms when active funds were exposed to higher risks of size and profitability, funds outperformed even when using S&P-SADITR as a proxy for market returns. It appears that funds' investment style during this period paid off the risks taken and compensated their subscribers with excessive abnormal returns (alpha).

Active funds exhibited significant performance variations between the periods before and after financial reforms. Table 5.11 highlights that, before financial reforms, active mutual funds recorded remarkably positive and significant alphas of 0.6%, 0.63% and 0.43% against the three indices, TASI, MSCI-SADI and S&P-SADITR, respectively. However, this exceptional performance diminished after the implementation of financial reforms. Consequently, this study fails to reject Hypothesis 2.H for the period before financial reforms, while it is rejected for the period following the implementation of financial reforms. This finding suggests that the significant risk-adjusted return performance (alpha) observed for the overall sample period is predominantly attributable to the period before financial reforms.

Significantly, this study is potentially the first to reveal evidence of the association between financial reforms and mutual fund performance in the Saudi Arabian market. The empirical findings about the existence of extraordinary alpha before financial reforms and its subsequent disappearance align with those of prior studies indicating that the Saudi Arabian stock market exhibited weak-form inefficiency during the period before financial reforms (Al-Ajmi & Kim, 2012; Budd, 2012; Butler & Malaikah, 1992; Syed & Bajwa, 2018). The observed disappearance of mispricing opportunities after financial reforms suggests a potential change in market efficiency. This robust inference from the present study calls for a re-evaluation of weak-form inefficiency of the Saudi Arabian market after financial reforms, as evidence in finance literature suggests improvement in market efficiency after significant events. For instance, Fama and French (1988a) attributed significant negative autocorrelations in 3-to-5-year US equity returns (weak-form inefficiency) during 1926–1985 to the period preceding 1940. Similarly, Fama and French (1989) suggested that the predictability of equity returns and bond spreads was significant during the Great Depression and post-World War II recessions. In the following subsection, further analysis of the active fund risk-adjusted performance during the overall sample period versus the performance before and after financial reforms will further highlight the significant disparity in active fund performance during these two periods.

Table 5.11

Time-Series Regressions of Active Fund Risk Premiums on the FFC6FM in the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Panel A: TASI returns represent market returns						
Variable	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
TASI-RP	0.79122***	0.75365***	0.76195***	0.78854***	0.82595***	0.76548***
	(0.02587)	(0.03871)	(0.05629)	(0.04909)	(0.04883)	(0.03114)
SMB	0.12262***	0.15461***	0.08493**	0.19536***	0.08775**	0.16724***
	(0.03258)	(0.05577)	(0.04169)	(0.04141)	(0.04091)	(0.04781)
HML	0.02541	-0.00083	0.05287	-0.06006	-0.03344	0.03449
	(0.03450)	(0.07058)	(0.04760)	(0.05243)	(0.04933)	(0.05097)
RMW	0.04782	0.02250	0.02541	0.05878	0.08519**	0.06223
	(0.03433)	(0.05929)	(0.04076)	(0.05746)	(0.03976)	(0.05424)
CMA	-0.04404	-0.00568	-0.05736	-0.02007	-0.03791	-0.0297
	(0.03884)	(0.10629)	(0.04328)	(0.05782)	(0.03283)	(0.06818)
MOM	0.02534	0.09962	0.00255	0.06930	-0.03152	0.06659
	(0.03644)	(0.07034)	(0.03706)	(0.07744)	(0.04960)	(0.04247)
Cons	0.00241**	0.00096	0.00346	0.00289	0.00601***	-0.00142
	(0.00113)	(0.00246)	(0.00256)	(0.00274)	(0.00137)	(0.00165)
R^2	0.9345	0.9412	0.8000	0.9118	0.9401	0.9441
F-statistic	214.16	126.64	37.78	94.63	95.11	167.08
Obs.	132	45	75	57	66	66
VIF	1.4	1.7	1.5	1.38	1.65	1.67

Table 5.11 (Continued)

Panel B: MSCI-SADI returns represent market returns						
Variable	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
MSCI-SADI-RP	0.76796***	0.78524***	0.7580***	0.78985***	0.83627***	0.74972***
	(0.02747)	(0.04299)	(0.06434)	(0.04628)	(0.03401)	(0.03581)
SMB	0.17382***	0.16813***	0.1441***	0.2299***	0.10677***	0.22722***
	(0.03528)	(0.05043)	(0.04633)	(0.04581)	(0.03437)	(0.04925)
HML	0.04232	0.03588	0.10388**	-0.06133	-0.07724	0.06995
	(0.03851)	(0.06016)	(0.05265)	(0.05599)	(0.04773)	(0.05170)
RMW	0.04995	-0.01179	0.0123	0.09280*	0.12746***	0.02845
	(0.03655)	(0.05682)	(0.04075)	(0.05502)	(0.04690)	(0.05791)
CMA	-0.04874	-0.14095	-0.09542**	0.04277	0.00544	-0.08701
	(0.04281)	(0.09348)	(0.04506)	(0.0836)	(0.03876)	(0.07382)
MOM	0.00318	0.11853	-0.03932	0.12492	0.00652	0.02399
	(0.03675)	(0.07408)	(0.03526)	(0.07837)	(0.04149)	(0.03985)
Cons	0.00207*	0.00148	0.00102	0.00345	0.00632***	-0.00225
	(0.00120)	(0.0022)	(0.00249)	(0.00247)	(0.0014)	(0.00172)
R^2	0.9251	0.9444	0.8080	0.9042	0.9392	0.9392
F-statistic	192.73	124.55	39.81	95.79	138.54	134.25
Obs.	132	45	73	59	66	66
VIF	1.39	1.72	1.49	1.36	1.69	1.66

Table 5.11 (Continued)

Panel C: S&P-SADITR returns represent market returns						
Variable	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
S&P-SADITR-RP	0.77443***	0.73185***	0.75225***	0.77806***	0.80097***	0.75398***
	(0.02635)	(0.03919)	(0.05237)	(0.05145)	(0.05029)	(0.03222)
SMB	0.13257***	0.15721***	0.10375**	0.19049***	0.09033**	0.18427***
	(0.03127)	(0.05168)	(0.04203)	(0.04170)	(0.03590)	(0.04656)
HML	0.01926	-0.03298	0.05300	-0.06904	-0.03139	0.03101
	(0.03291)	(0.06366)	(0.04595)	(0.05138)	(0.04683)	(0.05220)
RMW	0.04566	-0.01228	0.02460	0.06304	0.07429*	0.06569
	(0.03408)	(0.06172)	(0.04045)	(0.05591)	(0.03994)	(0.05181)
CMA	-0.02744	0.00373	-0.05446	0.02420	-0.01593	-0.02888
	(0.03905)	(0.10016)	(0.04252)	(0.07106)	(0.03074)	(0.06786)
MOM	0.03596	0.14187*	-0.00319	0.13541	-0.00851	0.07386
	(0.03783)	(0.07772)	(0.03537)	(0.08602)	(0.04419)	(0.04554)
Cons	0.00036	-0.00170	0.00072	0.00068	0.0043***	-0.00382**
	(0.00115)	(0.00236)	(0.00257)	(0.00273)	(0.00141)	(0.00168)
R^2	0.9348	0.9434	0.8155	0.9160	0.9428	0.9445
F-statistic	206.37	134.06	43.31	99.33	93.76	162.88
Obs.	132	45	77	55	66	66
VIF	1.4	1.7	1.52	1.34	1.65	1.67

Note. The dependent variable is the active mutual fund risk premium measured as these funds' unadjusted returns minus the rate of returns of the one-month SAMA bills (risk-free rate of returns). The independent variables are *TASI-RP*, *MSCI-SADI-RP*, S&P-*SADITR-RP*, *SMB*, *HML*, *RMW*, *CMA* and *MOM*. *TASI-RP*, *MSCI-SADI-RP* and *S&P-SADITR-RP* represent the stock market risk premium. In Panel A, *TASI-RP* is the TASI risk premium measured as the TASI returns minus the one-month SAMA bill rate of returns. In Panel B, *MSCI-SADI-RP* is the MSCI-SADI risk premium measured as the MSCI-SADI returns minus the one-month SAMA bill rate of returns. In Panel C, *S&P-SADITR-RP* is the S&P-SADITR risk premium measured as the S&P-SADITR returns minus the one-month SAMA bills rate of returns. *SMB* is the difference in the returns of the small stock portfolios and the large stock portfolios; *HML* is the difference in the returns of the portfolios with a high book-to-market ratio and a low book-to-market ratio; *RMW* is the difference in the returns of the portfolios with a robust operating income ratio and a weak operating income ratio; *CMA* is the difference in the returns of the portfolios with a conservative asset-growth ratio and an aggressive asset-growth ratio; *MOM* is the difference in the returns of the portfolios of winner stocks and loser stocks. The regressions are estimated against each market return separately for each sample period. Model (1) analyses the data for the overall sample period; Model (2) analyses the data for the financial crisis periods; Model (3) analyses the data for the bullish market periods; Model (4) analyses the data for the bearish market periods; Model (5) analyses the data for the period before equity market financial reforms; and Model (6) analyses the data for the period after these reforms. The variance inflation factor (VIF) monitors multicollinearity in regression models. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.2.1.2 Performance Variation Between the Overall Sample Period and Subsample Periods

The section explores whether there are variations in the active fund risk-adjusted performance during the overall sample period as against the periods of SMEs. Hypothesis 2.I was developed to test whether active fund risk-adjusted performance in subsample periods differed from that during the entire sample period. To test Hypothesis 2.I, the study applies the Wald test for equality of coefficients to compare the estimated risk-adjusted return performance during the overall sample period to that of subsample periods. This analysis shows whether active funds perform better during SMEs than in normal times or vice versa.

A significant Wald statistic indicates a considerable difference between the risk-adjusted return performance of the overall sample period and subsample periods. If the estimated risk-adjusted performance for the overall sample period is higher (lower) than that for a subsample period, it can be concluded that the risk-adjusted performance for the overall sample period is significantly better (worse) than that for the subsample period. Thus, this analysis clarifies whether active funds perform better or worse during SMEs.

Table 5.12 presents the results, which reveal significant differences between the risk-adjusted return performance during the overall sample period and before and after financial reforms. That is, the risk-adjusted performance of active funds for the period preceding financial reforms was significantly higher than that for the overall period. In contrast, the estimated risk-adjusted performance of active funds after financial reforms was significantly lower than that for the overall period. These findings hold true across the three risk-adjusted returns measured against TASI, MSCI-SADI and S&P-SADITR. Consequently, the statistical results fail to reject Hypothesis 2.I, indicating that active fund risk-adjusted return performance significantly varies for the periods before and after financial reforms compared with the overall period. However, the study rejects Hypothesis 2.I for other subsample periods, suggesting no significant difference in risk-adjusted return performance during these periods.

For a robustness check, the study further confirms the change in mutual fund risk-adjusted performance after financial reforms (July 2015) by testing for a structural break. Two structural break tests are applied for further analysis. First, the Wald (1943) structural break test confirms a significant change in active fund risk-adjusted performance after the financial reforms ($\chi^2 = 10.93$, p-value = 0.0009). Second, the Andrews (1993) test for a structural break with an unknown break date[33] yields significant statistics ($\chi^2 = 10.93$ and p-value = 0.0171) and remarkably identifies the break point in active fund risk-adjusted returns precisely in July 2015. These robust results underscore the pronounced impact of financial reforms on the performance of active mutual funds.

5.4.2.1.3 Performance Variation Across Benchmark Indices.

This section investigates potential variations in the risk-adjusted performance of active funds, when derived from three different benchmark indices serving as proxies for market returns. The pair-comparison of risk-adjusted performance include those based on TASI – MSCI-SADI, TASI – S&P-SADITR and MSCI-SADI – S&P-SADITR. To test Hypothesis 2.J, the Wald test for equality of coefficients is employed to discern whether the estimated risk-adjusted performance adjusted by using one proxy of market return is significantly different from that adjusted by using the other. A significant Wald statistic based on the chi-squared distribution indicates a considerable difference between such performance that is adjusted based on two different market returns. As a result, it can be concluded that there is variation in the inference of the risk-adjusted performance of active funds when using different market return proxies.

[33] The test is a function of the sample statistics computed over a range of prospective break points.

The results presented in Table 5.13 indicate that across the overall sample period, the financial crisis period and the periods before and after the financial reforms, the risk-adjusted performance of active funds measured based on TASI and MSCI-SADI is significantly higher than that adjusted by S&P-SADITR. However, there is no significant difference between the risk-adjusted performance measured based on TASI and that measured based on MSCI-SADI. Consequently, the statistical results fail to reject Hypothesis 2.J, suggesting that the inference of risk-adjusted performance of active funds varies when using TASI and MSCI-SADI in comparison to S&P-SADITR. However, Hypothesis 2.J is rejected when using TASI in comparison to MSCI-SADI.

This section has emphasised the crucial impact of selecting a market return proxy on the inference of active fund risk-adjusted performance. The findings reflect the importance of applying an appropriate benchmark index to proxy market returns. Since this study has examined active fund performance through two different approaches, benchmark-adjusted performance and risk-adjusted performance, using different proxies for market returns, it can be concluded that the findings demonstrate that when the same benchmark is used, the different performance measures (benchmark-adjusted performance and risk-adjusted performance) generally lead to similar inference. Conversely, when different benchmarks are used, the inferences drawn from the same measure can vary.[34] This observation about the effect of selecting a market return proxy on the inference of fund performance corresponds with the findings of Grinblatt and Titman (1994) regarding US mutual funds.

[34] TASI and MSCI-SADI generally yield similar inferences. However, S&P-SADITR leads to conclusions that differ from those of TASI and MSCI-SADI.

Table 5.12

Results of the Wald Statistic Comparing Active Fund Alpha Coefficients Between the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Index	Overall-FC		Overall-Bullish		Overall-Bearish		Overall –Before FRs		Overall-After FRs	
TASI	0.00241	0.00096	0.00241	0.00346	0.00241	0.00289	0.00241	0.00601	0.00241	-0.00142
	χ^2=0.34		χ^2=0.15		χ^2=0.03		χ^2= 10.10***		χ^2=3.44*	
MSCI-SADI	0.00207	0.00148	0.00207	0.00102	0.00207	0.00345	0.00207	0.00632	0.00207	-0.00225
	χ^2=0.06		χ^2= 0.14		χ^2=0.27		χ^2=12.72***		χ^2=4.27**	
S&P-SADITR	0.00036	-0.0017	0.00036	0.00072	0.00036	0.00068	0.00036	0.0043	0.00036	-0.00382
	χ^2= 0.69		χ^2= 0.02		χ^2=0.01		χ^2=11.32***		χ^2=4.08**	

Note. The table presents active mutual fund risk-adjusted returns (alpha) for the overall sample period and each subsample period (SMEs); below them, it also presents the Wald statistic for the test for equality of coefficients of alphas between the overall sample period and each subsample period. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that the coefficients are equal and accepts its alternative hypothesis that these are not equal. The FC stands for financial crises, Bullish stands for bullish market conditions, Bearish stands for bearish market conditions, Before FRs stands for before the 2015 financial reforms and After FRs stands for after the 2015 financial reforms. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.13

Results of the Wald Statistic Comparing Active Fund Alpha Coefficients Derived From Different Benchmark Indices

Index	Overall sample		Financial Crisis		Bullish market		Bearish market		Before financial reforms		After financial reforms	
	TASI	MSCI SADI	TASI	MSCI SADI	TASI	MSCIS ADI	TASI	MSCIS ADI	TASI	MSC SADI	TASI	MSCI SADI
MSCI-SADI	χ^2=0.2	--	χ^2=0.1	--	χ^2=0.64	--	χ^2=0.03	--	χ^2=0.07	--	χ^2=1.1	--
S&P-SADITR	χ^2=42.4 ***	χ^2=5.3 **	χ^2=32.5 ***	χ^2=4.22 **	χ^2=1.0	χ^2=0.01	χ^2=1.7	χ^2=0.6	χ^2=15.9 ***	χ^2=2.64 *	χ^2=30.6 ***	χ^2=4.1 **

Note. The table presents results for the Wald test for equality of coefficients of alphas that are derived from two different benchmark indices. The pair-comparison includes alphas that are based on TASI – MSCI-SADI, TASI – S&P-SADITR and MSCI-SADI – S&P-SADITR. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that the coefficients are equal and accepts its alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.2.2 Passive Mutual Funds

5.4.2.2.1 Risk-Adjusted Return Performance

Passive funds are designed to replicate the market's performance through an investment style that aims to closely track market returns and risks while minimising costs. Consequently, their risk-adjusted return performance primarily considers market risk. Following the literature, this study employs the SFM (Equation 4) to estimate risk-adjusted return performance, testing Hypothesis 2.K for passive funds. To apply the model, the study initially groups passive fund risk premiums (response variables) into equally weighted portfolios, forming time-series returns as explained in Chapter 4. Subsequently, its sets the risk premium of the market (TASI, MSCI-SADI and S&P-SADITR). With the model estimated, the alpha or constant of the model is calculated as the average of unexplained variations of the model. A positive and significant alpha indicates that funds outperform the market, while a negative and significant alpha indicates that funds underperform the market. Passive funds are not expected to outperform or underperform the market. However, in practice, passive fund performance might deviate from market performance due to factors such as management fees, dividends, cash holding and replication strategy (Charupat & Miu, 2013).

The risk premiums of passive funds (fund returns minus the risk-free rate of return) are regressed on market risk premiums. Table 5.14 reports the model estimations, with TASI in Panel A, MSCI-SADI in Panel B and S&P-SADITR in Panel C representing the market risk premium. The results demonstrate that the SFM effectively explains a high proportion of passive fund return variations. Specifically, the R-squared values indicate that the model accounts for passive funds' return variations across the overall sample period and subsample periods, ranging from 78.7% to 95.9% when TASI is used as the market proxy, 75.5% to 94.5% with MSCI-SADI and 82.5% to

97.1% with S&P-SADITR. These findings suggest that the three benchmark indices approximately explain equivalent levels of passive fund return variations. The *F*-statistics emphasise the high statistical significance of all regression models.

The estimates also shed light on the different behaviour towards market risk between passive and active funds. Passive funds exhibit greater sensitivity to market risk, aligning with their investment style. Their market betas, as shown in Table 5.14, range between 81% to 100% (against TASI), 80.5% to 100% (against MSCI-SADI) and 80.6% to 100% (against S&P-SADITR). In contrast, the market betas of active funds, as seen in Table 5.11, range between 75.4% to 82.5% (against TASI), 75% to 83.6% (against MSCI-SADI) and 73.2% to 80.1% (against S&P-SADITR). Generally, passive funds exhibit higher market betas than active funds, indicating that they more closely track market returns and risks, while active funds are exposed to other multiple risk factors based on their specific investment styles.

The model estimation does not yield any statistical evidence of significant outperformance of passive funds against TASI or MSCI-SADI. The alphas in Panels A and B of Table 5.14 indicate that passive funds tend to underperform TASI and MSCI-SADI, although this underperformance is not statistically significant in either the overall sample period or any subsample period. These results align with those of past studies on both developed and emerging markets (Khan et al., 2015). Panel C reports passive funds' performance against S&P-SADITR, an index that includes constituents' cash dividends in its returns. The results show evidence of significant underperformance by passive funds against S&P-SADITR. For instance, passive funds significantly underperformed S&P-SADITR by −0.32%, −0.25% and −0.47% during the overall sample period, the pre-financial-reform period and the post-financial-reform period, respectively. These results reject Hypothesis 2.K against all benchmark indices, indicating that passive funds do not generate positive and significant returns. These results are in line with those of Shin and Soydemir (2010), who found significant underperformance of a passive fund sample from America, Europe and Asia. The findings are also consistent with those of Diaw (2019) regarding the Saudi market, who found that passive funds underperformed the market. In conclusion, passive funds align with their investment style by closely tracking market returns and risks. However, the slight underperformance may be attributed to management costs.

Table 5.14

Time-Series Regressions of Passive Fund Risk Premiums on the SFM for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Panel A	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before Reforms	(6) After Reforms
TASI-RP	0.90937***	0.93219***	0.91619***	0.91094***	1.044***	0.81086***
	(0.03888)	(0.06085)	(0.08924)	(0.08657)	(0.03333)	(0.04154)
Cons	-0.00084	0.00144	-0.0012	-0.00064	-0.00036	-0.00227
	(0.00131)	(0.00283)	(0.00312)	(0.00314)	(0.00129)	(0.00193)
R^2	0.9178	0.9169	0.7871	0.8539	0.9585	0.9035
F-statistic	546.87	234.66	105.39	110.71	980.84	380.85
Obs.	132	45	75	57	66	66
Panel B	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before Reforms	(6) After Reforms
MSCI-SADI-RP	0.8981***	0.94287***	0.89646***	0.91178***	1.0184***	0.80541***
	(0.0404)	(0.06321)	(0.0899)	(0.08848)	(0.05055)	(0.0451)
Cons	-0.00117	0.00255	-0.0013	-0.00032	-0.00004	-0.00304
	(0.00143)	(0.00286)	(0.0033)	(0.00301)	(0.00171)	(0.00213)
R^2	0.9033	0.9027	0.7548	0.8275	0.9446	0.8847
F-statistic	494.54	222.44	99.30	106.18	405.70	318.87
Obs.	132	45	73	59	66	66
Panel C	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before Reforms	(6) After Reforms
S&P-SADITR-RP	0.8976***	0.91241***	0.9009***	0.90477***	1.01517***	0.80671***
	(0.03326)	(0.05142)	(0.07136)	(0.07504)	(0.02571)	(0.03696)
Cons	-0.0032***	-0.00128	-0.00348	-0.00269	-0.00252**	-0.00473**
	(0.00123)	(0.00262)	(0.00271)	(0.00273)	(0.00109)	(0.00187)
R^2	0.9305	0.9303	0.8248	0.8721	0.9710	0.9126
F-statistic	727.95	314.79	159.35	145.35	1559.03	476.19
Obs.	132	45	77	55	66	66

Note. The dependent variable is the passive mutual fund risk premium measured as these funds' unadjusted returns minus the rate of returns of the one-month SAMA bills (risk-free rate of returns). The independent variables are *TASI-RP*, *MSCI-SADI-RP*, S&P-*SADITR-RP*, *SMB*, *HML*, *RMW*, *CMA* and *MOM*. *TASI-RP*, *MSCI-SADI-RP* and *S&P-SADITR-RP* represent the stock market risk premium. In Panel A, *TASI-RP* is the TASI risk premium measured as the TASI returns minus the one-month SAMA bill rate of returns. In Panel B, *MSCI-SADI-RP* is the MSCI-SADI risk premium measured as the MSCI-SADI returns minus the one-month SAMA bill rate of returns. In Panel C, *S&P-SADITR-RP* is the S&P-SADITR risk premium measured as the S&P-SADITR returns minus the one-month SAMA bills rate of returns. *SMB* is the difference in the returns of the small stock portfolios and the large stock portfolios; *HML* is the difference in the returns of the portfolios with a high book-to-market ratio and a low book-to-market ratio; *RMW* is the difference in the returns of the portfolios with a robust operating income ratio and a weak operating income ratio; *CMA* is the difference in the returns of the portfolios with a conservative asset-growth ratio and an aggressive asset-growth ratio; *MOM* is the difference in the returns of the portfolios of winner stocks and loser stocks. The regressions are estimated against each market return separately for each sample period. Model (1) analyses the data for the overall sample period; Model (2) analyses the data for the financial crisis periods; Model (3) analyses the data for the bullish market periods; Model (4) analyses the data for the bearish market periods; Model (5) analyses the data for the period before equity market financial reforms; and Model (6) analyses the data for the period after these reforms. The variance inflation factor (VIF) monitors multicollinearity in regression models. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.2.2.2 Performance Variation Between Overall Sample Period and Subsample Periods

This subsection examines Hypothesis 2.L that investigates whether passive fund risk-adjusted performance during the overall sample period differed from that during periods of SMEs by applying the Wald test for equality of coefficients to compare the estimated performance during these periods. If the Wald statistic is more (less) than the statistical significance level in the chi-squared distribution, the test fails to reject (rejects) the hypothesis that there is considerable difference between the risk-adjusted return performance of the overall sample period and subsample periods. The results presented in Table 5.15 indicate that there was no significant difference in passive fund risk-adjusted performance during the overall sample period and during the subsample periods. This finding implies that passive funds consistently track their benchmark indices, maintaining a similar level of risk-adjusted performance across different market conditions. The rejection of Hypothesis 2.L suggests that the behaviour of passive funds in terms of risk-adjusted performance remains relatively stable, regardless of variations in market conditions or events. Investors relying on these funds for market exposure can thus expect a consistent risk-adjusted performance over different periods, as indicated by the study's findings.

5.4.2.2.3 Performance Variation Across Benchmark Indices

This section investigates potential variations in the risk-adjusted performance of passive funds, when derived from three different benchmark indices serving as proxies for market returns. The pair-comparison of risk-adjusted performance includes those based on TASI – MSCI-SADI, TASI – S&P-SADITR and MSCI-SADI – S&P-SADITR. To test Hypothesis 2.M, the study employs the Wald test for equality of coefficients to examine whether the estimated risk-adjusted performance, adjusted using one proxy of market return is significantly different from that adjusted using the other. A significant Wald statistic based on the chi-squared distribution indicates a considerable difference between such performance that is adjusted based on two different market return proxies. As a result, it can be concluded that there is variation in the risk-adjusted performance inference of active funds when using different market return proxies.

The results presented in Table 5.16 suggest that there is variation in the risk-adjusted performance evaluation of passive funds when different proxies of market returns are used. Specifically, during the overall sample period, periods of financial crises and periods before and after financial reforms, passive fund risk-adjusted performance is significantly higher when measured using TASI and MSCI-SADI than when measured using S&P-SADITR. However, there is no significant difference between risk-adjusted performance measured based on TASI and that measured based on MSCI-SADI. These findings support the importance of selecting an appropriate benchmark index to represent market returns accurately when evaluating passive fund performance.

In conclusion, the study's findings emphasise that the choice of a market return proxy can significantly affect the inferences drawn regarding passive fund risk-adjusted performance. These findings highlight the importance of using suitable benchmark indices for accurate performance assessment. Investors and researchers should carefully consider the implications of selecting different market proxies, as it can influence the conclusions drawn about the performance of both active and passive funds.

Table 5.15

Results of the Wald Statistic Comparing Passive Fund Alpha Coefficients Between the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Index	Overall-FC		Overall-Bullish		Overall-Bearish		Overall-Before		Overall-After	
TASI	-0.00083	0.00143	-0.00083	-0.00119	-0.00083	-0.00063	-0.00083	-0.00036	-0.00083	-0.00226
	χ^2= 0.52		χ^2= 0.01		χ^2= 0.00		χ^2= 0.14		χ^2=0.34	
MSCI-SADI	-0.00116	0.00254	-0.00116	-0.0012	-0.00116	-0.00031	-0.00116	-0.00004	-0.00116	-0.00304
	χ^2= 1.34		χ^2= 0.00		χ^2= 0.06		χ^2= 0.57		χ^2=0.46	
S&P-SADITR	-0.00321	-0.00128	-0.00321	-0.00348	-0.00323	-0.00269	-0.0032	-0.00252	-0.00321	-0.00473
	χ^2= 0.43		χ^2= 0.01		χ^2= 0.03		χ^2= 0.32		χ^2=0.43	

Note. The table presents passive mutual fund risk-adjusted returns (alpha) for the overall sample period and each subsample period (SMEs); below them, it also presents the Wald statistic for the test for equality of coefficients of alphas between the overall sample period and each subsample period. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that the coefficients are equal and accepts its alternative hypothesis that these are not equal. The FC stands for financial crises, Bullish stands for bullish market conditions, Bearish stands for bearish market conditions, Before FRs stands for before the 2015 financial reforms and After FRs stands for after the 2015 financial reforms. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.1*6*

Results of the Wald Statistic Comparing Passive Fund Alpha Coefficients Derived From Different Benchmark Indices

	Overall sample		Financial Crisis		Bullish market		Bearish market		Before financial reforms		After financial reforms	
	TASI	MSCI SADI	TASI	MSCI SADI	TASI	MSCI SADI	TASI	MSCI SADI	TASI	MSCI SADI	TASI	MSCI SADI
MSCI-SADI	χ^2=0.15	--	χ^2=0.42	--	χ^2=0.00	--	χ^2=0.00	--	χ^2=0.04	--	χ^2=0.60	--
S&P-SADITR	χ^2=52.25 ***	χ^2=5.82 **	χ^2=16.96 ***	χ^2=5.75 **	χ^2=2.10	χ^2=0.39	χ^2=0.49	χ^2=0.33	χ^2=15.4 ***	χ^2=2.48	χ^2=43.4 ***	χ^2=2.82 *

Note. The table presents results for the Wald test for equality of coefficients of alphas that are derived from two different benchmark indices. The pair-comparison includes alphas that are based on TASI – MSCI-SADI, TASI – S&P-SADITR and MSCI-SADI – S&P-SADITR. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that the coefficients are equal and accepts its alternative hypothesis that these are not equal. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.2.3 Comparison Between Active and Passive Funds

The preceding two sections analysed the risk-adjusted performance of active and passive funds independently. However, this section will engage into a comparative analysis, specifically focusing on comparing the risk-adjusted performance between active and passive funds. The formal approach in past studies was to exclusively rely on benchmark indices to evaluate mutual fund performance. However, indices are merely paper portfolios and not actual investable assets. Moreover, they do not incur any management costs, as noted by Frino and Gallagher (2001). Consequently, utilising benchmark indices to represent passive management in the analysis of active fund performance might lead to an underestimation of estimated performance, given that indices do not bear any management costs. In light of these considerations, this section adopts an unconventional approach to compare the risk-adjusted performance of active funds with that of passive funds. This approach takes into account the investable opportunities in passive fund management and considers the associated costs for each fund category.

Hypothesis 2.N examines the potential difference in estimated alphas between active funds and passive funds. To test this hypothesis, the study employs Weesie's (1999) seemingly unrelated regression method, simultaneously estimating alphas for both active and passive funds. Subsequently, a Wald test is applied to examine whether the difference between the estimated alphas of active funds and passive funds significantly deviates from zero. A significant (non-significant) result of the Wald test indicates that the risk-adjusted returns of active funds are significantly higher (lower) than that of passive funds. To standardise the comparison, the risk-adjusted performance of active and passive funds was estimated and analysed separately by using the SFM (see Table 5.17) and the FFC6FM (see Table 5.18).

Overall, the findings have demonstrated a superior performance of active funds over passive funds. Tables 5.17 and 5.18 compare the risk-adjusted returns of active and passive funds when estimated based on the SFM and FFC6FM, respectively. The results in Table 5.17 demonstrate a positive and significant difference between the returns of active funds and passive funds. Moreover, these results are robust across the three benchmarks: TASI, MSCI-SADI and S&P-SADITR. Specifically, active fund alpha exceeded passive fund alpha by significant monthly returns of 0.380%, 0.385% and 0.409%, respectively. The analysis of subsample periods shows that active fund risk-adjusted returns are also significantly higher than that of passive funds for the period before the financial reforms. For this sample period, there is a positive and significant difference between alphas of 0.630%, 0.621% and 0.679%, respectively.

Similarly, the results in Table 5.18 show a positive and significant difference between the risk-adjusted returns of active and passive funds, and the results are robust across the three benchmarks used. Notably, active funds, even after adjusting for their additional risks, can still outperform passive funds. To illustrate, active fund alpha surpassed passive fund alpha during the overall sample period by significant returns of 0.309%, 0.313% and 0.343%, respectively. Moreover, during the pre-financial-reform period, active fund alpha was higher than that of passive funds by a significant difference of 0.616%, 0.605% and 0.671%, respectively. The statistical results that the alpha of active funds is significantly higher than that of passive funds fail to reject Hypothesis 2.N that active fund risk-adjusted performance significantly differs from passive fund risk-adjusted performance. These findings remain robust and consistent when alphas are estimated using both the SFM and the FFC6FM. Hypothesis 2.N can be rejected for other subsample periods since there is insufficient evidence of a statistically significant difference in alphas.

Upon comparing the current results with the findings in the literature, it becomes evident that the current results mostly contradict those of prior studies conducted on developed markets and correspond with those of studies on other emerging markets. Crane and Crotty (2018) showed evidence from the US market that a small group of active funds can generate significant risk-adjusted performance, but this outperformance is in a similar proportion to that of passive funds. This finding suggests that risk-averse investors should not invest in a random active fund over a random passive fund. Pace et al. (2016) compared the risk-adjusted return performance of groups of active funds to their comparable passive funds in the US and Europe. As they found non-significant alphas, they concluded that there is no difference between the performance of active and passive funds based on a simple comparison. However, the tests conducted in the present study showed a statistically significant difference between active and passive alphas in Saudi Arabia. Conversely, similarly to this study's conclusion, Shreekant et al. (2020) found that during the period 2006–2019, there was a significant difference between the Jensen alpha of active funds and passive funds in India. The conflicting conclusions of Crane and Crotty (2018) and Pace et al. (2016) on one side, and Shreekant et al. (2020) and the present results on the other side, are consistent with the findings of Huij and Post (2011), who reported that active mutual funds perform better in emerging markets than in developed markets.

This study is the first to provide empirical evidence of active mutual fund performance in comparison to passive mutual fund performance in Saudi Arabia. Some past studies on Saudi Arabian mutual funds found evidence of active mutual fund performance that challenges the EMH. They found that active mutual funds outperformed the market returns that were proxied using benchmark indices (Al Rahahleh & Bhatti, 2022; Alqadhib et al., 2022). Similarly to past studies, the empirical results of this study challenge EMH. However, this study contributes to the portfolio management literature by adding empirical evidence of the superiority of active management over an investable passive management.

Table 5.17

Alpha Coefficients of Active and Passive Funds Based on the SFM, and Alpha Differences Between Active and Passive Funds for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

	TASI		MSCI-SADI		S&P-SADITR	
	Alpha	Model R^2	Alpha	Model R^2	Alpha	Model R^2
Overall sample period						
Active funds	0.00297**	0.9196	0.00268**	0.8950	0.00088	0.9177
Passive funds	-0.00084	0.9178	-0.00117	0.9033	-0.00321***	0.9305
Alpha difference	0.00380**		0.00385**		0.0041**	
	χ^2=5.21		χ^2=5.33		χ^2=5.68	
Financial crisis period						
Active funds	0.00388	0.9183	0.00488*	0.9111	0.00141	0.9104
Passive funds	0.00144	0.9169	0.00255	0.9027	-0.00128	0.9303
Alpha difference	0.00244		0.00234		0.00269	
	χ^2=0.43		χ^2=0.38		χ^2=0.53	
Bullish market period						
Active funds	0.00517**	0.7751	0.00315	0.7260	0.00214	0.7800
Passive funds	-0.0012	0.7871	-0.0013	0.7548	-0.00348	0.8248
Alpha difference	0.00637*		0.00444		0.00563	
	χ^2=3.72		χ^2=1.48		χ^2=2.59	
Bearish market period						
Active funds	0.00372	0.8588	0.00658**	0.8367	0.00305	0.8642
Passive funds	-0.00064	0.8539	-0.00032	0.8275	-0.00269	0.8721
Alpha difference	0.00435		0.00689*		0.00575	
	χ^2=0.81		χ^2=2.8		χ^2=1.57	
Before financial reforms						
Active funds	0.00594***	0.9273	0.00617***	0.9215	0.00427***	0.9320
Passive funds	-0.00036	0.9585	-0.00004	0.9446	-0.00252**	0.9710
Alpha difference	0.00631***		0.00622***		0.00679***	
	χ^2=11.21		χ^2=10.20		χ^2=13.02	

	TASI		MSCI-SADI		S&P-SADITR	
	Alpha	Model R^2	Alpha	Model R^2	Alpha	Model R^2
After financial reforms						
Active funds	-0.00011	0.9196	-0.00088	0.8827	-0.00251	0.9142
Passive funds	-0.00227	0.9035	-0.00304	0.8847	-0.00473**	0.9126
Alpha difference	0.00216		0.00217		0.00222	
	χ^2= 0.81		χ^2=0.81		χ^2=0.80	

Note. The table compares risk-adjusted return performance based on the SFM of active funds to that of passive funds during the overall sample period and each subsample period. Alpha difference is the difference in alphas of active funds and passive funds. It also presents the Wald statistic for the test for equality of coefficients of alpha difference, hypothesising that alpha coefficients are equal. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that coefficients are equal and accepts its alternative hypothesis that coefficients are not equal. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.18

Alpha Coefficients of Active and Passive Funds Based on the FFC6FM, and Alpha Differences Between Active and Passive Funds for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

	TASI		MSCI-SADI		S&P-SADITR	
	Alpha	Model R^2	Alpha	Model R^2	Alpha	Model R^2
Overall sample period						
Active funds	0.00241**	0.9345	0.0021*	0.9251	0.00036	0.9348
Passive funds	-0.00069	0.9205	-0.00107	0.9076	-0.00307**	0.9324
Alpha difference	0.00309*		0.00314*		0.00343*	
	χ^2= 3.23		χ^2=3.31		χ^2=3.74	
Financial crisis period						
Active funds	0.00096	0.9412	0.00148	0.9444	-0.0017	0.9434
Passive funds	0.00298	0.9427	0.00323	0.9199	-0.00023	0.9468
Alpha difference	-0.00202		-0.00174		-0.00147	
	χ^2=0.39		χ^2=0.28		χ^2=0.20	
Bullish market period						
Active funds	0.00346	0.8000	0.00102	0.8080	0.00072	0.8155
Passive funds	-0.00214	0.7944	-0.00291	0.7912	-0.00483	0.8331
Alpha difference	0.00561*		0.00394		0.00555	
	χ^2=2.76		χ^2=0.96		χ^2=2.50	
Bearish market period						
Active funds	0.00289	0.9118	0.00345	0.9042	0.00068	0.9160
Passive funds	0.00237	0.8816	0.00115	0.8448	-0.00035	0.8969
Alpha difference	0.00052		0.0023		0.00104	
	χ^2=0.02		χ^2=0.50		χ^2=0.09	
Before financial reforms						
Active funds	0.00601***	0.9401	0.00632***	0.9392	0.0043***	0.9428
Passive funds	-0.00015	0.9622	0.00026	0.9514	-0.00242**	0.9745
Alpha difference	0.00617***		0.00606***		0.00672***	

	TASI		MSCI-SADI		S&P-SADITR	
	Alpha	Model R^2	Alpha	Model R^2	Alpha	Model R^2
	χ^2=12.52		χ^2=11.74		χ^2=15.41	
After financial reforms						
Active funds	-0.00142	0.9441	-0.00225	0.9392	-0.00382	0.9445
Passive funds	-0.00233	0.9171	-0.00316	0.9061	-0.00477	0.9266
Alpha difference	0.00090		0.0091		0.00095	
	χ^2= 0.13		χ^2=0.13		χ^2=0.13	

Note. The table compares risk-adjusted return performance based on the FFC6FM of active funds to that of passive funds during the overall sample period and each subsample period. Alpha difference is the difference in alphas of active funds and passive funds. It also presents the Wald statistic for the test for equality of coefficients of alpha difference, hypothesising that alpha coefficients are equal. The significance of the Wald statistic is determined through the chi-squared distribution. If the Wald statistic is more extreme than the critical value in the chi-squared distribution, this test rejects its null hypothesis that coefficients are equal and accepts its alternative hypothesis that coefficients are not equal. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

5.4.3 Market Timing Performance Analysis

This section investigates mutual fund managers' ability to improve their performance through market timing. In the preceding section, the models were employed to identify the aggregate abnormal return performance of the funds. This performance stems from a combination of micro-forecasting skills, which involves acquiring undervalued stocks and shorting overvalued ones, and macro-forecasting skills. The latter skills entail the strategic allocation of assets based on forecasts of market direction, a practice commonly referred to as market timing. Jensen (1972) highlighted the inherent challenge in applying the specifications of the SFM (and, similarly, of multi-factor models) to separate the incremental performance attributable to stock-picking skills from that attributable to market timing skills. This section assesses whether outperformance is attributed to securities selection, market timing or both. To examine Hypothesis 2.O, the study applies two key models from the literature to measure the market timing abilities of mutual fund managers: the Treynor and Mazuy (1966) and Henriksson and Merton (1981) models.

First, Treynor and Mazuy (1966) developed their model by building upon the specifications of the SFM in order to assess the capability of fund managers to strategically time major market fluctuations and thus outperform the market. Treynor and Mazuy argued that portfolio managers reallocate the composition of their portfolios, shifting from high-volatility stocks to low-volatility stocks in anticipation of a bearish market, and vice versa for an expected bullish market. According to Treynor and Mazuy, fund managers who accurately predict market direction would adhere to a quadratic characteristic line (convex function) instead of the straight characteristic line of the SFM. A significant and positive (non-significant and negative) coefficient of the quadratic line signifies the presence (absence) of market timing skills. Second, Henriksson and Merton (1981) built upon Merton's (1981) theoretical framework to develop a model based on the SFM that captures fund managers' ability to time the market. Henriksson and Merton argued that portfolio managers who anticipate a bearish market would adopt a protective put option investment strategy equal to their investment in the equity market. The model assumes that mutual fund managers would exercise these options in a bear market, thereby generating returns that are equivalent. A positive and significant coefficient of the protective put option variable indicates that fund managers possess accurate market timing skills, while a negative or non-significant coefficient suggests a lack thereof. In essence, both the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model are key models that have found extensive application in this field (J. Gao et al., 2020; Oliveira et al., 2019; Zeeshan et al., 2020).

5.4.3.1 Treynor and Mazuy (1966) Model

The Treynor and Mazuy (1966) model employs a regression framework, whereby active mutual fund risk premium (excess returns) is regressed on the market risk premium, the squared returns of this premium, and risk factors based on the FFC6FM settings. In this model, the intercept coefficient is indicative of stock selectivity skills, while the coefficient of gamma in Equations (15) and (16) represents market timing skills. Table 5.19 presents the model's estimations in its original form settings, while Table 5.20 reports the estimations based on the FFC6FM framework. In Panel A, TASI-RP, in Panel B, MSCI-SADI, and in Panel C, S&P-SADITR represent the model's estimations with different proxies of market risk premiums (market excess returns).

The *R*-squared results indicate that the model explains a substantial portion of mutual fund return variations across sample periods. Specifically, when TASI is used as a proxy for market returns, the model explains variations ranging from 78.73% to 92.9%. Similarly, when MSCI-SADI is applied as the market return proxy, the model explains variations ranging from 75.7% to 92.5%, and when S&P-SADITR is used, the model explains variations ranging from 80% to

93.3%. These results suggest that the three benchmark indices explain almost equivalent levels of mutual fund return variations. Furthermore, the *F*-statistics demonstrate the statistical significance of all regression models, indicating the robustness of the Treynor and Mazuy (1966) model across different market return proxies.

The results in Table 5.19 and Table 5.20 reveal that active mutual funds in Saudi Arabia possess stock selectivity skills but lack market timing skills. On applying the original form of the Treynor and Mazuy (1966) model in Table 5.19, the results show that active funds gained positive and significant alpha of 0.4% and 0.4617% against TASI and MSCI-SADI, respectively, in the overall sample period. Similarly, they produced 0.45% and 0.647% against TASI and MSCI-SADI for the period before the financial reforms. More importantly, the coefficients of market timing skills reveal that active mutual funds did not possess market timing skills during any sample period. Across the three market proxies, TASI, MSCI-SADI and S&P-SADITR, the market timing coefficients tend to be negative and significant. The results on using MSCI-SADI to represent the market show that active mutual funds recorded the highest negative and significant coefficient of −0.6294 during the overall sample period.

Similar findings are observed by applying the Treynor and Mazuy (1966) model within the framework of FFC6FM in Table 5.20. The findings demonstrate that active funds achieved positive and significant alphas of 0.324% and 0.355% against TASI and MSCI-SADI, respectively, in the overall sample period. Similarly, they significantly outperformed TASI and MSCI-SADI by 0.453% and 0.618% for the period before the financial reforms. Remarkably, the market timing coefficients consistently demonstrate that active mutual funds lacked market timing skills throughout all sample periods. Across the three market proxies, TASI, MSCI-SADI and S&P-SADITR, these coefficients did not exhibit any positive and statistically significant values.

The statistical results provide evidence to reject Hypothesis 2.O and to conclude that active mutual funds did not possess market timing skills during the overall sample period or any subsample periods according to the Treynor and Mazuy (1966) model. Overall, it can be observed from Table 5.19 and Table 5.20 that the negative and significant coefficients for market timing skills persist during financial crises, bullish market periods, bearish market periods and after financial reforms across the three indices. These results are consistent with the results in the market timing literature (Merdad et al., 2016; Zouaoui, 2019).

Table 5.19

Evaluation of Fund Managers' Stock Selectivity and Market Timing Skills Using the Treynor and Mazuy (1966) Model for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
Panel A: Mutual funds are benchmarked against TASI						
Selectivity skills coefficient	0.0040***	0.00617**	0.00086	0.00212	0.00451**	0.00211
	(0.00131)	(0.00301)	(0.00406)	(0.00361)	(0.00182)	(0.00197)
Market timing coefficient	-0.34112	-0.59227*	-2.2254**	-0.44636	0.55366	-0.6493***
	(0.25836)	(0.34815)	(0.96156)	(0.73641)	(0.54041)	(0.22447)
R^2	0.9211	0.9227	0.7873	0.8596	0.9297	0.9263
F-statistic	588.24	344.40	213.49	110.57	277.29	505.81
Obs.	132	45	75	55	66	66
Panel B: Mutual funds are benchmarked against MSCI-SADI						
Selectivity skills coefficient	0.00462***	0.00922***	-0.00529	0.00190	0.00647***	0.00186
	(0.00147)	(0.00306)	(0.00360)	(0.00381)	(0.00201)	(0.00233)
Market timing coefficient	-0.62949***	-1.1207***	-4.2031***	-1.63119**	-0.11244	-0.8011***
	(0.24257)	(0.27349)	(1.37212)	(0.81143)	(0.5453)	(0.29643)
R^2	0.8994	0.9252	0.7571	0.8448	0.9216	0.8916
F-statistic	622.51	531.70	85.24	310.27	482.14	350.49
Obs.	132	45	73	59	66	66
Panel C: Mutual funds are benchmarked against S&P-SADITR						
Selectivity skills coefficient	0.00199	0.00425	-0.00437	0.00355	0.00327*	-0.00021
	(0.00131)	(0.00308)	(0.00442)	(0.00327)	(0.00176)	(0.00208)
Market timing coefficient	-0.34484	-0.65232*	-3.08636**	0.14485	0.357335	-0.64144**
	(0.28741)	(0.37416)	(1.2222)	(0.81263)	(0.62263)	(0.25381)
R^2	0.9192	0.9165	0.8006	0.8642	0.9333	0.9206
F-statistic	551.34	311.64	125.99	95.67	192.33	443.98
Obs.	132	45	77	55	66	66

Note. Selectivity and market timing skills of active mutual funds are measured using the Treynor and Mazuy (1966) model based on the SFM settings. The benchmarks are TASI in Panel A, MSCI-SADI in Panel B and S&P-SADITR in Panel C. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.20

Evaluating Fund Managers' Stock Selectivity and Market Timing Skills: A Treynor and Mazuy (1966) Model Approach Within the Framework of FFC6FM for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

Panel A: Mutual funds are benchmarked against TASI						
	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
Selectivity skills coefficient	0.00324***	0.00273	-0.00058	0.00173	0.00453***	0.00023
	(0.00123)	(0.00323)	(0.00368)	(0.00405)	(0.00163)	(0.00191)
Market timing coefficient	-0.25904	-0.42672	-2.33043**	-0.31363	0.58101	-0.42247
	(0.26825)	(0.39921)	(1.0852)	(0.75425)	(0.54529)	(0.26011)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9352	0.9429	0.8107	0.9121	0.9426	0.9463
F statistic	194.01	98.41	54.08	72.20	104.24	150.37
Obs.	132	45	75	55	66	66

Panel B: Mutual funds are benchmarked against MSCI-SADI						
Selectivity skills coefficient	0.00355***	0.00480	-0.00580**	-0.00004	0.00618***	-0.00042
	(0.00125)	(0.00311)	(0.00283)	(0.00333)	(0.00178)	(0.00182)
Market timing coefficient	-0.45933*	-0.7735**	-3.7275***	-1.3356*	0.04964	-0.47634
	(0.24646)	(0.38555)	(1.11357)	(0.71505)	(0.55193)	(0.29789)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9271	0.9494	0.8297	0.9087	0.9392	0.9417
F statistic	209.42	168.90	40.25	80.46	149.36	153.23
Obs.	132	45	73	59	66	66

Panel C: Mutual funds are benchmarked against S&P-SADITR						
Selectivity skills coefficient	0.00107	-0.00027	-0.00509	0.00116	0.00316*	-0.00245
	(0.00127)	(0.00328)	(0.00365)	(0.00370)	(0.00164)	(0.00192)
Market timing coefficient	-0.20680	-0.30135	-2.94388**	0.13785	0.4089	-0.33614
	(0.28067)	(0.37079)	(1.1542)	(0.68114)	(0.59911)	(0.2610)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9353	0.9444	0.8310	0.9160	0.9444	0.9459
F statistic	191.30	103.64	39.32	89.58	88.75	139.84
Obs.	132	45	77	55	66	66

Note. Selectivity and market timing skills of active mutual funds are measured using the Treynor and Mazuy (1966) model based on the FFC6FM settings. The benchmarks are TASI in Panel A, MSCI-SADI in Panel B and S&P-SADITR in Panel C. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.3.2 Henriksson and Merton (1981) Model

The Henriksson and Merton (1981) model employs a regression framework, whereby active mutual fund risk premium is regressed on the market risk premium, the squared returns of market risk premium, and risk factors based on the FFC6FM settings. In this model, the intercept coefficient is indicative of stock selectivity skills, while the coefficient of gamma in Equations (17) and (18) represents market timing skills. Table 5.21 presents the model's estimations in its original form settings, while Table 5.22 reports the estimations based on the FFC6FM framework. In Panel A, TASI-RP, in Panel B, MSCI-SADI, and in Panel C, S&P-SADITR represent the model's estimations with different proxies of market risk premiums.

The *R*-squared outcomes show that the model explains a considerable proportion of the fluctuations in mutual fund returns throughout various periods. Specifically, when TASI serves as a proxy for market returns, the model explains variations ranging from 77.5% to 92.9%. Likewise, with MSCI-SADI employed as the proxy, the model explains variations ranging from 72.6% to 92.1%, and when S&P-SADITR is utilised, it explains variations ranging from 78% to 93.3%. These findings suggest that the three benchmark indices explain nearly equivalent levels of mutual fund return variations. In addition, the *F*-statistics underscore the statistical significance of all regression models, affirming the robustness of the Treynor and Mazuy (1966) model across different market return proxies.

The results presented in Table 5.21 and Table 5.22 indicate that active mutual funds in Saudi Arabia possess stock selectivity skills but lack the ability to time the market effectively. Table 5.21 shows that on applying the original Henriksson and Merton (1981) model, active funds demonstrate positive and statistically significant alpha values of 0.449% and 0.486% against TASI and MSCI-SADI, respectively, over the entire sample period. Similarly, they generate alpha values of 0.892%, 1.197% and 0.741 against TASI, MSCI-SADI and S&P-SADITR, respectively, during periods of financial crises. Most importantly, the coefficients representing market timing skills reveal that active mutual funds do not possess the ability to time the market in any of the sample periods. Across the three market proxies, the market timing coefficients consistently exhibit negative values.

Consistent results are found when applying the Henriksson and Merton (1981) model within the context of FFC6FM, as shown in Table 5.22. The results reveal that active funds generate positive and statistically significant alpha values of 0.327% and 0.303% against TASI and MSCI-SADI, respectively, over the entire sample period. Notably, the market timing coefficients consistently indicate that active mutual funds lacked market timing skills across all sample periods. Across all the market proxies, these coefficients tend to be negative and often statistically non-significant.

To sum up, in both Table 5.21 and Table 5.22, a consistent pattern emerges, with negative coefficients for market timing skills persisting not only during financial crises but also after financial reforms across the three indices. Consequently, the statistical findings offer compelling evidence to reject Hypothesis 2.O on the grounds of the Henriksson and Merton (1981) model. It can be concluded that active mutual funds did not exhibit market timing skills during the overall sample period or any of the subsample periods.

Table 5.21

Evaluation of Fund Managers' Stock Selectivity and Market Timing Skills Using the Henriksson and Merton (1981) Model for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
Panel A: Mutual funds are benchmarked against TASI						
Selectivity skills coefficient	0.00449**	0.00892**	0.00517*	0.00371	0.00355	0.00371
	(0.00191)	(0.00432)	(0.00265)	(0.00278)	(0.00265)	(0.00266)
Market timing coefficient	-0.07309	-0.20608*	N/A	N/A	0.11740	-0.17880**
	(0.0787)	(0.11766)			(0.12611)	(0.07871)
R^2	0.9204	0.9235	0.7751	0.8588	0.9290	0.9248
F-statistic	556.99	361.92	186.41	221.65	269.69	517.79
Obs.	132	45	75	55	66	66
Panel B: Mutual funds are benchmarked against MSCI-SADI						
Selectivity skills coefficient	0.00486**	0.01197***	0.003145	0.00657**	0.00561*	0.00288
	(0.00204)	(0.00398)	(0.00282)	(0.00290)	(0.00307)	(0.00283)
Market timing coefficient	-0.10298	-0.28951***	N/A	N/A	0.02661	-0.17695*
	(0.0811)	(0.09979)			(0.13068)	(0.09519)
R^2	0.8965	0.9211	0.7260	0.8367	0.9216	0.8879
F-statistic	476.42	393.67	136.87	314.92	399.61	255.91
Obs.	132	45	73	59	66	66
Panel C: Mutual funds are benchmarked against S&P-SADITR						
Selectivity skills coefficient	0.00255	0.00741*	0.00214	0.00305	0.00245	0.00135
	(0.00194)	(0.00441)	(0.00269)	(0.00282)	(0.00267)	(0.00283)
Market timing coefficient	-0.07781	-0.23232*	N/A	N/A	0.08699	-0.17604**
	(0.08310)	(0.12260)			(0.14307)	(0.08352)
R^2	0.9186	0.9177	0.7800	0.8642	0.9331	0.9193
F-statistic	507.15	310.31	205.62	165.34	189.56	470.28
Obs.	132	45	77	55	66	66

Note. Selectivity and market timing skills of active mutual funds are measured using the Henriksson and Merton (1981) model based on the SFM settings. The benchmarks are TASI in Panel A, MSCI-SADI in Panel B and S&P-SADITR in Panel C. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.22

Evaluation of Fund Managers' Stock Selectivity and Market Timing Skills: A Henriksson and Merton (1981) Model Approach Within the Framework of FFC6FM for the Overall Sample Period (January 2010 – December 2020) and Subsample Periods

	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before FRs	(6) After FRs
Panel A: Mutual funds are benchmarked against TASI						
Selectivity skills coefficient	0.00327*	0.00453	0.00346	0.00289	0.00329	0.00092
	(0.00180)	(0.00489)	(0.00256)	(0.00274)	(0.0025)	(0.00242)
Market timing coefficient	-0.04025	-0.13914	N/A	N/A	0.13482	-0.10197
	(0.0789)	(0.14451)			(0.1303)	(0.0785)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9347	0.9429	0.8000	0.9118	0.9422	0.9454
F statistic	187.42	99.39	37.78	94.63	104.03	164.66
Obs.	132	45	75	55	66	66
Panel B: Mutual funds are benchmarked against MSCI-SADI						
Selectivity skills coefficient	0.00303*	0.00575	0.00102	0.00344	0.00447	-0.00017
	(0.00177)	(0.00430)	(0.00249)	(0.00247)	(0.00280)	(0.00227)
Market timing coefficient	-0.04429	-0.16582	N/A	N/A	0.08814	-0.09171
	(0.0778)	(0.1261)			(0.1324)	(0.088)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9253	0.9470	0.8080	0.9042	0.9401	0.9404
F statistic	177.78	127.72	39.81	95.79	128.88	141.33
Obs.	132	45	73	59	66	66
Panel C: Mutual funds are benchmarked against S&P-SADITR						
Selectivity skills coefficient	0.00108	0.00119	0.00072	0.00116	0.00211	-0.00196
	(0.0018)	(0.0049)	(0.0025)	(0.0037)	(0.0026)	(0.0024)
Market timing coefficient	-0.03260	-0.10596	N/A	N/A	0.10480	-0.07869
	(0.0800)	(0.1361)			(0.1426)	(0.07931)
FFC6FM	Yes	Yes	Yes	Yes	Yes	Yes
R–sqr	0.9349	0.9445	0.8155	0.9160	0.9442	0.9453
F statistic	182.50	104.57	43.31	99.33	89.54	153.97
Obs.	132	45	77	55	66	66

Note. Selectivity and market timing skills of active mutual funds are measured using the Henriksson and Merton (1981) model based on the FFC6FM settings. The benchmarks are TASI in Panel A, MSCI-SADI in Panel B and S&P-SADITR in Panel C. The Newey–West (1986) heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5.4.3.3 Overall Fund Market Timing Ability in Saudi Arabia

In general, the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model have both demonstrated consistent and robust findings, that active mutual funds in Saudi Arabia exhibit stock selectivity skills and lack market timing skills. This conclusion is drawn from the negative and significant market timing coefficients observed in both models. However, several explanations could account for these results.

First, mutual fund managers may inaccurately anticipate future market movements, and even if they successfully forecast market directions, they might miss the opportune moment for action. Second, the high transaction costs associated with increased trading activities during market fluctuations may affect mutual fund market timing performance negatively. Third, perverse timing behaviour might arise if managers prioritise stock selectivity performance at the expense of market timing performance (Volkman, 1999). Fourth, Edelen (1999) suggested that subscribers anticipate upward markets, leading to increased inflows before upward markets. The slow allocation of these inflows results in higher cash levels, reducing the portfolio’s beta and consequently leading to negative market timing.

Fifth, Bollen and Busse (2001) argued that market timing decisions require high-frequency adjustments. Thus, the analysis of monthly frequency commonly used in the literature, including in this study, might fail to capture the contribution of a manager’s timing ability. Sixth, Matallín-Sáez et al. (2015) suggested that the asymmetric correlation phenomenon in stock markets may contribute to significant and negative market timing coefficients. Grounded in prior empirical evidence supporting the existence of this phenomenon owing to which stock correlations are higher during bear market periods than in bull market periods, their explanation rests on two elements. One is the automatic shifts in stocks’ betas. In bear markets, the average stocks’ covariance increases more than the variance of the market, resulting in an overall elevation of all stocks' betas. The other is the covariance dispersion map, which shows that the distribution of the difference in these shifts of stocks' betas becomes more concentrated during bear markets.

The present study suggests that the negative and significant market timing coefficients might be attributable to an asymmetric correlation phenomenon in the Saudi Arabian stock markets. Specifically, the analysis has indicated that active mutual fund returns are more sensitive to market factors during bearish market periods across the three indices. Nonetheless, this study acknowledges that there is no empirical evidence in the literature of an asymmetric correlation phenomenon in Saudi Arabia's stock market to support this assumption. Therefore, additional focused research is warranted to better understand the underlying reasons for these negative and significant market timing coefficients in the Saudi market context, which leaves room for future research to explore this issue.

5.5 Chapter Summary

This chapter focused on achieving two primary research objectives. First, it aimed to evaluate the efficacy of models employed in measuring mutual fund performance, specifically identifying the most effective models within the Saudi Arabian context. By considering the latest models, it assessed their ability to explain mutual fund returns. The accuracy of a model in explaining mutual fund returns directly correlates with its effectiveness in measuring performance or unexplained returns (alpha). The study compared five pricing models—SFM, FF3FM, FFC4FM, FF5FM and FFC6FM—with the objective of ranking them according to their efficiency in explaining mutual fund returns. The empirical results of the GRS F-test statistic, GRS J-test statistic and MAA have demonstrated that the FFC6FM is the most efficient model for measuring mutual fund performance. This model effectively incorporates the market, size, value, profitability, investment and momentum risk factors, providing a more accurate explanation of returns in mutual fund portfolios. These results demonstrate the importance of adjusting mutual funds' returns to these risk factors for measuring risk-adjusted performance. Conversely, using incomplete models that do not control for these risk factors may overestimate the actual risk-adjusted performance (alpha) of mutual funds. This investigation contributes to the literature on asset pricing models by testing the models on the actual returns of mutual fund. The empirical results, encompassing the GRS F-test statistic, GRS J-test statistic and MAA, unequivocally point to FFC6FM as the most efficient model for estimating mutual fund performance. This model efficiently incorporates the market, size, value, profitability, investment and momentum risk factors, providing a more accurate explanation of returns in mutual fund portfolios. These outcomes underscore the significance of adjusting mutual fund returns for these risk factors when measuring risk-adjusted performance.

The second research objective involved a comprehensive examination of active and passive mutual fund performance in Saudi Arabia, divided into five sub-objectives. The first sub-objective involved investigating the benchmark- and risk-adjusted performance of active and passive funds. The mean-difference measure was used to assess the benchmark-adjusted performance, while the FFC6FM and SFM were applied to estimate the risk-adjusted performance of active and passive funds, respectively. Overall, the findings suggest that active funds outperformed the market, whereas there is no compelling evidence supporting such outperformance of passive funds.

The second sub-objective investigates whether active and passive fund performance varied during SMEs compared with the overall sample period. The two-sample *t*-test and the Wald test for equality of coefficients were employed for comparison. The findings show that the benchmark-adjusted performance of active funds during financial crises, and bearish (and bullish) market conditions is significantly higher (lower) than their performance during the overall sample period. Furthermore, the risk-adjusted performance of active funds before the 2015 financial reforms was significantly higher than that during the overall sample period, suggesting changes in the performance of active funds post the financial reforms. These results indicate that active fund managers' strategies may respond differently to SMEs, allowing investors to capitalise on the fluctuating nature of active fund performance. In contrast, the benchmark-adjusted performance and risk-adjusted performance of passive funds both behaved consistently during SMEs, as they did during the overall sample period, emphasising their strategy of closely tracking benchmark indices at all times, resulting in consistent performance regardless of SMEs.

The third sub-objective involved comparing the performance of active funds with that of passive funds. The comparisons, based on the benchmark- and risk-adjusted return performance, revealed the significant superiority of active funds over passive funds. The fourth sub-objective explored the potential impact of selecting different benchmark indices as proxies for market returns on the inference of mutual fund performance. The findings show that when the same benchmark is used, different performance measures generally yield similar inferences. Conversely, when different benchmarks are used, the inferences drawn from the same measure vary. The fifth sub-objective was to examine the market timing skills of active fund managers, which involved applying the Treynor and Mazuy (1966) and the Henriksson and Merton (1981) market timing models in their original forms and in the FFC6FM settings. Notably, the current study did not find sufficient evidence of mutual fund market timing skills in Saudi Arabia.

Chapter 6: Analysis of Persistence of Mutual Fund Return Performance

6.1 Introduction

The previous chapter examined Hypothesis 2, focusing on the analysis of aggregate mutual fund performance. This chapter shifts the focus to Hypothesis 3, investigating whether the persistence of performance in individual mutual funds is attributable to stock-picking skills of fund managers or is merely the result of luck. The findings of aggregate fund outperformance in the previous chapter, along with the findings of past studies on the Saudi market (Al Rahahleh & Bhatti, 2022; Ashraf, 2013), do not necessary imply that most individual funds possess managerial skills. In this regard, Malkiel (2020) has shown that fund outperformance due to luck may also persist. Conversely, the findings of aggregate fund underperformance in some studies (BinMahfouz & Hassan, 2012; El-Mousallamy & El-Masry, 2016) also do not necessary imply that some fund managers lack stock-picking skills. Therefore, this chapter aims to investigate whether significant performance can truly be attributed to genuine fund managers' stock-picking skills in Saudi Arabia or is merely a result of pure luck.

Several approaches can be used to examine mutual fund performance persistence.[35] However, most of those models do not account for the dissimilarity of risk-taking among funds or potential non-normalities in fund alphas (Kosowski et al., 2006). To address this issue, Kosowski et al. (2006) developed a bootstrap statistical technique as a more reliable methodology to examine mutual fund performance persistence. This methodology provides improved inference in identifying fund managers with genuine skills by accounting for dissimilarity in risk-taking among

[35] They were discussed extensively in Section 3.6.

funds and the potential existence of non-normalities in fund alphas. Later, Fama and French (2010) modified this approach. Subsequently, the bootstrap statistical technique has gained significant application in the research area of mutual fund performance persistence (A.-S. Chen et al., 2012; Harvey & Liu, 2022; Huang et al., 2023; Kooli & Stetsyuk, 2021; Riley, 2019; Tapver, 2023; Yang & Liu, 2017).

The remainder of this chapter is organised as follows. Section 6.2 provides summary statistics that centre on the analysis of alpha values. Section 6.3 presents the main results on mutual fund performance persistence, and Section 6.3 analyses and discusses of the results. Section 6.4 concludes the chapter with a summary of key findings.

6.2 Descriptive Statistics of Alpha Value of Individual Active Funds

This section presents various statistics pertaining to the alpha values of individual active funds. It encompasses descriptive statistics, selected percentiles and the percentages of funds exhibiting significantly positive and negative alphas at different significance levels. These estimated alphas are indicative of a fund manager's ability to generate abnormal returns. Therefore, the insights derived from these statistics offer a comprehensive perspective on mutual fund performance, which is essential for the main analysis presented in the following section.

To estimate the alpha of individual funds, the study applied the FFC6FM (Equation 8), which has been discussed in Chapter 4, by regressing each fund's returns on the market returns along with other risk factors. The estimated intercept underlies the alpha (for further details of how the intercept represents abnormal returns, see Chapter 3).

6.2.1 Statistical Analysis of Alpha Values of Individual Funds for Overall Sample Period

Table 6.1 presents the descriptive statistics of individual funds' alpha estimates (in % per month) and the distribution of alpha estimates for chosen percentiles (in % per month) from

January 2010 to December 2020. The results in Panels A, B and C are funds' alpha estimates based on TASI, MSCI-SADI and S&P-SADITR as proxies of market returns, respectively. In Panel A, the mean alpha estimate is 0.143%, and it ranges between (−0.977 % and 2.06%), whereas the *t*-statistic of the mean alpha is 0.812, and it ranges between (−2.44 and 5.46). Turning to the distributions of alpha estimates for the chosen percentiles, funds within the median percentile (50^{th}) outperformed the market with a positive monthly alpha of 0.223%. The funds that fall within the 75^{th} and 90^{th} percentiles produced alphas that are relatively high, 0.386% and 0.628% per month net of all costs, respectively (4.73% and 7.8% annually). The funds that fall in the 95^{th} and 99^{th} percentiles delivered outstanding alphas of 0.664% and 0.845% per month net of all costs, respectively (8.7% and 10.6% annually). Moreover, funds in the bottom 1^{st} percentile generated significantly negative performance of −0.843% per month. The descriptive statistics of the alpha values in Panel B are relatively similar for those estimated based on TASI in Panel A. The mean alpha estimate is 0.103%, and it ranges between (−1.09 % and 1.97%), whereas the *t*-statistic of the mean alpha is 0.633, and it ranges between (−2.57 and 5.05). The alpha estimates for the chosen percentiles are almost identical because those are estimated based on TASI in Panel A.

However, in Panel C, the statistics of alpha estimates and the *t*-statistics of alphas are quite different when S&P-SADITR is applied as the market return proxy. The mean alpha estimate is negative (−0.058%), and it ranges between (−1.149 % and 1.814%), whereas the *t*-statistic of the mean alpha is −0.104, and it ranges between (−2.76 and 4.08). The funds within the median percentile underperformed the market with a slightly negative monthly alpha of −0.031%, which means that after deducting all management costs, fund subscribers are not better off by investing in the funds within the median percentile. The funds that fall within the 75^{th} and 90^{th} percentiles generated alphas that are fairly reasonable at 0.147% and 0.425% per month net of all costs, respectively (1.77% and 5.22% annually). The funds in 95th and 99th percentiles delivered significant risk-adjusted performance of 0.4916% and 0.844% per month net of all costs, respectively (6.06% and 10.6% annually). Conversely, the funds in the bottom 1st percentile generated significantly negative performance of −1.033% per month (−13.12% annually).

Overall, when funds' alphas are estimated against TASI and MSCI-SADI, the alphas are tilted towards positive values, which means that after deducting all management costs, fund subscribers are better off by investing in the funds within the median percentile. Conversely, when funds' alphas are estimated against S&P-SADI, fund subscribers lose about −0.031% by investing in the funds within the median percentile.

Table 6.1

Summary Statistics of Alpha Values of Individual Active Funds (January 2010 – December 2020)[36]

	Panel A: TASI				Panel B: MSCI-SADI				Panel C: S&P-SADITR			
Variable	*M*%	*SD* %	Min%	Max%	*M*%	*SD* %	Min%	Max%	*M*%	*SD*. %	Min%	Max%
Alpha (%)	0.1426	0.4215	-0.9771	2.059	0.1032	0.4240	-1.096	1.976	-0.058	0.409	-1.1491	1.8136
t-statistic of alphas	0.8118	1.4928	-2.44	5.46	0.6333	1.4295	-2.57	5.05	-0.105	1.231	-2.76	4.08
1st percentile	-0.8432				-0.8901				-1.0327			
5th percentile	-0.5440				-0.5782				-0.6916			
10th percentile	-0.3695				-0.4083				-0.5252			
25th percentile	-0.1537				-0.2141				-0.3119			
50th percentile	0.2233				0.1593				-0.0309			
75th percentile	0.3858				0.3566				0.1465			
90th percentile	0.6275				0.5783				0.4253			
95th percentile	0.6642				0.6364				0.4916			
99th percentile	0.8447				0.8435				0.8436			

Note. The first row presents the descriptive statistics of cross-sectional alpha estimates (in % per month); the second row presents the descriptive statistics of the t-statistics for cross-sectional alphas, followed by the distribution of alpha estimates for chosen percentiles (in % per month).

[36] Any fund that has less than 36 months of returns is removed from the analysis, leaving 109 active mutual funds from the sample of 120 active mutual funds.

Table 6.2 reports the percentage of funds with significant positive and significant negative alphas of individual funds at the 10%, 5% and 1% statistical significance levels from January 2010 to December 2020. It can be observed that when their returns are adjusted against TASI, 27.5% of funds delivered positive alphas whereas only 2.8% underperformed at the 10% statistical significance level. At the 5% level of significance, 20.2% of funds produced positive alphas whereas only 1.8% of funds underperformed. Moreover, 11% of the funds delivered positive alphas while no fund underperformed at the 1% statistical significance level. Similarly, when funds' returns are adjusted against MSCI-SADI, the number of funds that produced a significant positive alpha exceeds the number of those that produced significant negative alphas. In contrast, when funds' returns are adjusted against S&P-SADITR, only 4.6% of funds delivered positive alphas whereas 13.8% of funds underperformed at the 10% statistical significance level. At the 5% level of significance, 3.7% and 5.5% of funds produced positive alphas and negative alphas, respectively. Last, 1% of funds delivered positive and negative alphas at the 1% statistical significance level. These percentages reveal that the funds that significantly underperformed the market are more in number than the funds that significantly outperformed, when their returns are adjusted against S&P-SADITR.

In brief, the disparity in percentages of funds that outperformed and underperformed at different significance levels reveals that the number of funds that significantly outperformed the market exceeds the number of funds that significantly underperformed the market, specifically, when using alphas estimated against TASI and MSCI-SADI. These results confirm the results presented in Table 6.1 regarding the tilt of the 50th percentile of alphas towards positive values.

Table 6.2

Percentage of Funds That Outperformed and Underperformed the Market Based on Estimated Alphas (January 2010 – December 2020)

Benchmark indices	TASI	MSCI-SADI	S&P-SADITR
Percentage of outperforming funds (positive alpha)			
at 10% significance level	27.5	23.9	4.60
at 5% significance level	20.2	16.5	3.70
at 1% significance level	11.0	8.30	1.00
Percentage of underperforming funds (negative alpha)			
at 10% significance level	2.80	3.70	13.8
at 5% significance level	1.83	1.83	5.5
at 1% significance level	0.00	0.00	1.00
Number of funds	109	109	109

Note. This table displays the percentages of funds exhibiting positive and negative alphas at the significance levels of 10%, 5% and 1%. To clarify, the percentage of funds with positive alphas at the 10% significance level is determined by dividing the number of funds with positive alphas at this level by the total number of funds in the sample. Similarly, the percentage of funds with negative alphas at the 10% significance level is calculated by dividing the number of funds with negative alphas at this level by the total number of funds in the sample. Similar calculations are applied to determine the corresponding percentages at the 5% and 1% significance levels. These alphas are estimated against three benchmark indices: TASI, MSCI-SADI and S&P-SADITR.

6.2.2 Statistical Analysis of Alpha Values of Individual Funds (January 2010 – June 2015)

Table 6.3 presents the descriptive statistics of individual funds' alpha estimates (in % per month) and the distribution of the alpha estimates for chosen percentiles (in % per month) for the period before the 2015 financial reforms (January 2010 – June 2015). The results in Panels A, B and C are estimates based on TASI, MSCI-SADI and S&P-SADITR as proxies of market returns, respectively.

In Panel A, the mean alpha estimate is 0.558%, and it ranges between (−1.15 % and 1.85%), whereas the *t*-statistic of the mean alpha is 2.36, and it ranges between (−2.47 and 4.97). The distribution of alpha estimates for the chosen percentiles shows that funds that fall within the median percentile outperformed the market with a positive monthly alpha of 0.561%. The funds that fall within the 75th and 90th percentiles produced very high alphas of 0.74% and 1.06% per month net of all costs, respectively (9.25% and 12.8% annually). The funds that fall in the 95th and 99th percentiles delivered outstanding alphas of 1.58% and 1.85% per month net of all costs, respectively (20.7% and 24.7% annually). Moreover, the funds in the bottom 1st percentile generated significantly negative performance of −0.843% per month (−10.6% annually). In Panel B, the alpha statistics are relatively similar to those estimated based on TASI in Panel A. The mean alpha estimate is 0.586%, and it ranges between (−1.11 % and 1.87%), whereas the *t*-statistic of the mean alpha is 2.46, and it ranges between (−2.33 and 5.06). The alpha estimates in percentiles are very similar to those were estimated based on TASI in Panel A.

In Panel C, the mean alpha estimate is positive at 0.392%, and it ranges between (−1.244 % and 1.781%), whereas the *t*-statistic of the mean alpha is 1.573, and it ranges between (−2.67 and 4.61). The funds within the median percentile outperformed the market with a positive monthly alpha of 0.384%. The funds that fall within the 75th and 90th percentiles generated alphas that are fairly reasonable at 0.553% and 0.853% per month net of all costs, respectively (6.84% and 10.73% annually). The funds in 95th and 99th percentiles delivered significant alphas of 1.458% and 1.780% per month net of all costs, respectively (18.96% and 23.58% annually). Conversely, the funds in the bottom 1st percentile generated significantly negative performance of −1.244% per month (−16.0% annually).

Table 6.3

Summary Statistics of Alpha Values of Individual Active Funds (January 2010 – June 2015)[37]

	Panel A: TASI				Panel B: MSCI-SADI				Panel C: S&P-SADITR			
Variable	*M*%	*SD* %	Min%	Max%	*M*%	*SD* %	Min%	Max%	*M*%	*SD.* %	Min%	Max%
Alpha (%)	0.5586	0.4846	-1.1497	1.8536	0.5869	0.4877	-1.1119	1.8744	0.3921	0.4987	-1.2441	1.7807
t-statistic of alphas	2.3556	1.5894	-2.47	4.97	2.4685	1.5895	-2.33	5.06	1.5737	1.497	-2.67	4.61
1st percentile	-1.1497				-1.1119				-1.2441			
5th percentile	-0.2256				-0.1983				-0.4307			
10th percentile	-0.0155				-0.008				-0.2053			
25th percentile	0.3959				0.4220				0.1916			
50th percentile	0.5614				0.5931				0.3846			
75th percentile	0.7400				0.778				0.5537			
90th percentile	1.0576				1.0898				0.8536			
95th percentile	1.5795				1.6198				1.4588			
99th percentile	1.8536				1.8744				1.7807			

Note. The first row presents the descriptive statistics of cross-sectional alpha estimates (in % per month); the second row presents the descriptive statistics of the t-statistics for cross-sectional alphas, followed by the distribution of alpha estimates for chosen percentiles (in % per month).

[37] After removing any fund that has less than 36 months of returns in this subsample, 59 active mutual funds are left.

Table 6.4 reports the percentage of funds with the significant positive and significant negative alphas of individual funds at the 10%, 5% and 1% statistical significance levels from January 2010 to June 2015. The results show that when funds' returns are adjusted against TASI, 71.2% of funds delivered positive alphas, whereas only 1.7% of funds underperformed at the 10% statistical significance level. At the 5% significance level, 67.8% of funds produced positive alphas, whereas only 1.7% of funds underperformed. Moreover, 52.5% funds delivered positive alphas, while no fund underperformed at the 1% statistical significance level. When funds' returns are adjusted against MSCI-SADI, the statistics of alpha are almost identical to those estimated against TASI.

Furthermore, the statistics of alpha are moderately similar when they are estimated based on S&P-SADITR as the market return proxy—57.6% of funds delivered positive alphas, whereas only 3.4% underperformed at the 10% statistical significance level. At the 5% level of significance, 33.9% of funds produced positive alphas, whereas only 1.7% underperformed. Moreover, 23.8% delivered positive alphas, while no fund underperformed at the 1% statistical significance level.

Table 6.4

Percentage of Funds That Outperformed and Underperformed the Market Based on the Estimated Alphas (January 2010 – June 2015)

Benchmark indices	TASI	MSCI-SADI	S&P-SADITR
Percentage of outperforming funds (positive alpha)			
at 10% significance level	71.2	71.2	57.6
at 5% significance level	67.8	67.8	33.9
at 1% significance level	52.5	55.94	23.8
Percentage of underperforming funds (negative alpha)			
at 10% significance level	1.70	1.70	3.40
at 5% significance level	1.70	1.70	1.70
at 1% significance level	0.00	0.00	0.00
Number of funds	59	59	59

Note. This table displays the percentages of funds exhibiting positive and negative alphas at the significance levels of 10%, 5% and 1%. To clarify, the percentage of funds with positive alphas at the 10% significance level is determined by dividing the number of funds with positive alphas at this level by the total number of funds in the sample. Similarly, the percentage of funds with negative alphas at the 10% significance level is calculated by dividing the number of funds with negative alphas at this level by the total number of funds in the sample. Similar calculations are applied to determine the corresponding percentages at the 5% and 1% significance levels. These alphas are estimated against three benchmark indices: TASI, MSCI-SADI and S&P-SADITR.

In summary, as shown in Table 6.3, before the 2015 financial reforms, funds' alphas were significantly skewed towards positive values, exhibiting higher mean alphas than during the overall sample period. To illustrate, even after deducting all management costs, investors could have been better off by simply investing in any fund falling within the 25th percentile. Within this percentile, investors could gain a net profit ranging between 0.191% and 0.421%. The results in Table 6.4 have confirmed this significant skewness towards positive values among most funds, as these have revealed that the percentage of funds that significantly outperformed the market is considerably higher than the percentage of funds that significantly underperformed.

6.2.3 Statistical Analysis of Alpha Values of Individual Funds From July 2015 to December 2020

Table 6.5 presents the descriptive statistics of alpha estimates for the period after the financial reforms, that is, from July 2015 to December 2020. The results in Panels A, B and C are alpha estimates based on TASI, MSCI-SADI and S&P-SADITR as proxies of market returns, respectively.

In Panel A, the mean alpha estimate is −0.088%, and it ranges between −1.4% and 2.05%. The *t*-statistic of the mean alpha is −0.15, and it ranges between −2.78 and 3.5. The distribution of alpha estimates for the chosen percentiles shows that funds that fall within the median percentile underperformed the market with a negative monthly alpha of −0.076%. This means that investors in the median funds did not benefit from investing in these funds. The funds in the 75^{th} and 90^{th} percentiles produced positive alphas, but relatively, these are not very high, at 0.229% and 0.380% per month net of all costs, respectively (2.78% and 4.66% annually). The funds in the 95^{th} and 99^{th} percentiles delivered alphas of 0.568% and 0.674% per month net of all costs, respectively (7.04% and 8.4% annually). Conversely, the funds in the bottom 1^{st} percentile generated a negative alpha of 1.255% per month (−16.15% annually).

In Panel B, the mean alpha estimate is −0.166%, and it ranges between (−1.42 % and 1.97%), whereas the *t*-statistic of the mean alpha is −0.429, and it ranges between (−2.72 and 2.79). The distributions of alpha estimates over percentiles are very similar to those estimated based on TASI in Panel A. However, the estimates of alphas based on S&P-SADITR in Panel C are much lower as funds' returns were adjusted against an index with accumulative returns. The mean alpha estimate is a negative value of −0.320%, and it ranges between (−1.48 % and 1.81%), whereas the *t*-statistic of the mean alpha is −1.01, and it ranges between (−3.3 and 2.23). The funds within the median and 75th percentiles underperformed the market with a negative monthly alpha of −0.317% and −0.047%. The funds that fall within the 90th, 95th and 99th percentiles generated reasonable alphas of 0.117%, 0.330% and 0.425% per month net of all costs, respectively (1.41%, 4.03% and 5.22% annually). On the other side of the distribution, funds in the bottom 1st percentile generated a significantly negative performance of −1.457% per month (−18.96% annually).

Table 6.5

Summary Statistics of Alpha Values of Individual Active Funds (July 2015 – December 2020)

	Panel A: TASI				Panel B: MSCI-SADI				Panel C: S&P-SADITR			
Variable	*M*%	*SD* %	Min%	Max%	*M*%	*SD* %	Min%	Max%	*M*%	*SD*. %	Min%	Max%
Alpha (%)	-0.0886	0.4746	-1.4037	2.0596	-0.1665	0.4739	-1.4249	1.9762	-0.3201	0.4459	-1.4852	1.814
t-statistic of alphas	-0.1501	1.3325	-2.78	3.5	-0.4291	1.2534	-2.72	2.79	-1.0133	1.1604	-3.3	2.23
1st percentile	-1.2553				-1.3864				-1.4574			
5th percentile	-0.8029				-0.8593				-0.9746			
10th percentile	-0.6959				-0.7378				-0.8565			
25th percentile	-0.3878				-0.4357				-0.5879			
50th percentile	-0.0761				-0.1657				-0.3176			
75th percentile	0.2288				0.1352				-0.0471			
90th percentile	0.3804				0.3217				0.1179			
95th percentile	0.5685				0.5503				0.3301			
99th percentile	0.6743				0.7371				0.4260			

Note. The first row presents the descriptive statistics of cross-sectional alpha estimates (in % per month); the second row presents the descriptive statistics of the t-statistics for cross-sectional alphas, followed by the distribution of alpha estimates for chosen percentiles (in % per month).

Table 6.6 reports the percentage of funds with significant positive and significant negative alphas of individual funds at the 10%, 5% and 1% statistical significance levels from July 2015 to December 2020. When funds' returns are adjusted against TASI, only 5.9% funds delivered positive alphas, while 16.7% underperformed at the 10% statistical significance level. At the 5% level of significance, 3.9% of funds produced positive alphas, whereas 4.9% underperformed the market. Moreover, 2.9% delivered positive alphas, while 1% underperformed at the 1% statistical significance level. When funds' returns are adjusted against MSCI-SADI, the percentages of funds with significant positive and negative alphas are similar to the percentages when the returns are adjusted against TASI. However, when alphas are estimated based on S&P-SADITR as a proxy of market return, most of the funds underperformed the market at all statistical significance levels.

Table 6.6

Percentage of Funds That Outperformed and Underperformed the Market Based on the Estimated Alphas (July 2015 – December 2020)

Benchmark indices	TASI	MSCI-SADI	S&P-SADITR
Percentage of outperforming funds (positive alpha)			
at 10% significance level	5.90	3.92	2.94
at 5% significance level	3.92	2.94	2.0
at 1% significance level	2.94	2.00	0.00
Percentage of underperforming funds (negative alpha)			
at 10% significance level	16.70	16.70	36.27
at 5% significance level	4.90	9.80	21.57
at 1% significance level	1.00	2.0	4.90
Number of funds	102	102	102

Note. This table displays the percentages of funds exhibiting positive and negative alphas at the significance levels of 10%, 5% and 1%. To clarify, the percentage of funds with positive alphas at the 10% significance level is determined by dividing the number of funds with positive alphas at this level by the total number of funds in the sample. Similarly, the percentage of funds with negative alphas at the 10% significance level is calculated by dividing the number of funds with negative alphas at this level by the total number of funds in the sample. Similar calculations are applied to determine the corresponding percentages at the 5% and 1% significance levels. These alphas are estimated against three benchmark indices: TASI, MSCI-SADI and S&P-SADITR.

In conclusion, Table 6.5 has shown that after the 2015 financial reforms, fund alphas were skewed towards negative values, exhibiting a negative mean alpha that is lower than the mean alpha for the overall sample period. To illustrate, after deducting all management costs, investors need to invest in funds that fall within the 75^{th} or 90^{th} percentile to gain profits. Table 6.6 has confirmed this significant skewness towards negative values among most funds, as the table shows that the number of funds that significantly underperformed the market is much larger than the number of funds that significantly outperformed. The following subsection compares the alphas values for the two subsample periods.

6.2.4 Comparison Between Alpha Values for the Periods Before and After the Financial Reforms of 2015

Upon comparing the statistics of individual alpha estimates before and after the implementation of financial reforms, an evident and remarkable disparity is observed between the two periods. The mean value of alpha estimates severely declined from 0.558% in the period before financial reforms to −0.089% in the period after financial reforms. Furthermore, the mean value of the *t*-statistics of alphas decreased from 2.356 to −0.150, respectively. Regardless of the index used to estimate these values, generally, there are large declines in these estimates after the implementation of financial reforms across the three indices. The slump in the mean values of alpha and of the *t*-statistics of alphas after the implementation of the 2015 financial reforms is confirmed by the evident shift from the high percentage of significant positive performance before the financial reforms to the high percentage of significant negative performance after these reforms. The entry of QFIIs in 2015 into the Saudi market holds the potential to enhance market efficiency, thereby reducing or eliminating the mispricing opportunities available to active funds.

Further explanation about this steep shift in active mutual fund performance will be provided later in this chapter.

6.3 Empirical Analysis of Mutual Fund Performance Persistence

6.3.1 Normality of Individual Fund Alphas

Before proceeding to the main analysis of mutual fund performance persistence in the following subsection, the study applies the Shapiro and Francia (1972) normality test to analyse the distributions of individual fund residuals produced by the performance model of Equation (8) in Chapter 4. First, when TASI is applied as the market return proxy to estimate the performance, the results show that normality of individual fund residuals is rejected for 57%, 48% and 38% of funds at the 10%, 5% and 1% statistical significance levels, respectively. Moreover, when MSCI-SADI and S&P-SADITR are applied as proxies, quite similar results are obtained, as follows: For MSCI-SADI, the normality of individual fund residuals is rejected for 55%, 45% and 32% of funds, and for S&P-SADITR, it is rejected for 55%, 49% and 36% of funds, at the 10%, 5% and 1% statistical significance levels, respectively.

These robust results of non-normality among some individual fund residuals challenge the validity of earlier approaches to investigate mutual fund performance persistence that assume the existence of normality on individual fund residuals (for more details, see Chapter 3). Moreover, these findings present the importance of the bootstrap statistical technique in investigating the existence of the significance of true funds' alphas while controlling for the potential persistence of luck.

6.3.2 Bootstrap Analysis of the Significance of t-Statistic Estimates of Alphas

This section addresses Hypothesis 3 that examines the existence of managerial skills among a group of active mutual funds in Saudi Arabia. The results of fund aggregate performance in Chapter 5 have not confirmed whether significant performance results from managerial skills or merely luck, because funds with significantly positive alphas may be balanced by funds with significantly negative alphas. However, this chapter tests for persistence in active mutual fund return performance, that is, whether outperforming funds continue to outperform and underperforming funds continue to underperform. Various approaches are available for testing for such persistence, such as those of Grinblatt and Titman (1992) and Hendricks et al. (1993). However, given non-normality in the distributions of some individual fund alphas, the bootstrap statistical technique is preferred over the other methods as it can address this issue (Kosowski et al., 2006).

The bootstrap statistical technique compares the actual cross-section of t-statistic estimates of funds' alphas to the results from bootstrap simulations of the cross-section that have the properties of the actual t-statistic estimates of funds' alphas. The bootstrap approach has the following steps: First, apply FFC6FM to estimate t-statistic estimates of alphas of each fund in the sample, which provides a cross-section of t-statistic estimates of alphas. These cross-sections are to be arranged from the smallest to the largest into a cumulative distribution function. Second, using FFC6FM, run a simulation of mutual fund performance, as explained in Chapter 4, for each fund in the sample, which also provides a cross-section of the simulated t-statistic of alphas. These cross-sections of t-statistic of alphas from bootstrap simulations are similarly ordered from the smallest to the largest into a cumulative distribution function. The comparison between the actual cross-section of these estimates and the results from bootstrap simulations allows to draw inferences about the existence of skilful fund managers (Fama & French, 2010). Within the extreme right tail of the cross-section distributions,[38] if the actual t-statistic estimates of alphas have much more extreme positive values than those in the bootstrap iterations (the luck distribution), it can be concluded that luck is not the sole source of significant performance, and real skills exist. Likewise, within the extreme left tail of the cross-section distribution,[39] if the actual t-statistic estimates of alphas exceed those from bootstrap simulations, it can be inferred that bad luck is not the only source of significant negative alphas, and lack of managerial skills also exists.

It is important to note here why the inference of fund performance persistence was built upon the t-statistic estimates of alphas rather than the alpha estimates themselves. Although the analysis of the latter provides insights into individual funds' performance, the values of the former possess unique advantageous statistical properties in studying fund performance persistence. To illustrate, shorter-lived funds and funds that take higher levels of risk tend to have relatively larger alphas (S. Brown et al., 1992; Kosowski et al., 2006).[40] Therefore, Kosowski et al. (2006) suggested examining mutual fund performance persistence based on t-statistic estimates of alphas as it scales alpha values by their standard errors. Accordingly, this study focuses its main analysis of mutual fund performance persistence on t-statistic estimates of alphas.

Next, Subsection 6.3.2.1 presents the analysis for the overall sample period from January 2010 to December 2020. Subsections 6.3.2.2 and 6.3.2.3 present the analyses for the pre-reform period (January 2010 – June 2015) and for the post-reform period (July 2015 – December 2020),

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[38] The critical regions of *t*-value standard significance levels are 1.645, 1.960 and 2.576 at 10%, 5% and 1% statistical significance, respectively.

[39] The critical regions of *t*-value standard significance levels are −1.645, −1.960 and −2.576 at 10%, 5% and 1% statistical significance, respectively.

[40] Since funds have unequal lifetimes and usually assume disparate levels of risk, which both lead to a high variance-estimated alpha distribution, this high variance could bias the alpha values of these funds.

respectively. Last, Subsection 6.3.2.4 presents the comparison of the bootstrap analysis findings for these pre- and post-financial reform periods.

6.3.2.1 Bootstrap Analysis for Overall Sample Period (January 2010 – December 2020)

Table 6.7 presents the results of the actual t-statistic estimates of alphas and of alpha *t*-statistics from bootstrap simulations for January 2010 – December 2020 period. On using TASI and MSCI-SADI as market return proxies in estimations, the estimation results show that funds within the 80th percentile and above produced actual alpha *t*-statistic estimates of 2.02 and 1.84, which exceed the corresponding alpha *t*-statistics from bootstrap simulations of 1.32 and 1.32, respectively. Hypothesis 3.A assumes that significant alphas of individual funds are not a result of propitious luck, and that, rather, skilled fund managers exist. Therefore, the findings fail to reject Hypothesis 3.A that mutual funds outperform the market owing to investment skills, confirming the existence of managerial skills among the top 80th percentile of funds in Saudi Arabia. However, when S&P-SADITR is applied as the proxy for market returns to estimate alphas, the study finds that only funds within the top 99th percentile possess genuine stock-picking skills. The distinction arises from the fact that S&P-SADITR includes accumulated dividends from its constituents in its overall returns, rendering it a challenging index to outperform.

Figure 6.1 depicts the cumulative density function (CDF) of the cross-sectional distributions for both the actual t-statistic estimates of alphas and those from bootstrap simulations. The study's interest lies in determining the existence of funds with actual t-statistic estimates of alphas that are above a certain level of alpha compared with the bootstrapped distributions. The results of Figure 6.1 illustrate the observations from Table 6.7 that in the far-right tail, the t-statistic of alphas from bootstrap simulations lies below the actual t-statistic estimates of alphas in that region. The current findings contrast with those of Fama and French (2010), Tapver (2023) and

Yang and Liu (2017) who did not find evidence of the presence of skilled managers. The findings of this study correspond with those of A.-S. Chen et al. (2012), Cuthbertson et al. (2008) and Kosowski et al. (2006, 2007) that a group of skilled managers have sufficient talent in stock selection to deliver consecutive outperforming returns. This study's results are closest to those of Hammami and Oueslati (2017) who applied the bootstrap simulation approach to examine the stock-picking skills of fund managers of Islamic funds in GCC countries.

At the negative side of the performance scale, Table 6.7 shows that the alpha *t*-statistics of actual estimates exceed the corresponding values from the bootstrap simulation. For instance, in the 1st percentile, the actual t-statistic estimates of alphas are −2.16, −2.43 and −2.61 when the estimations were against TASI, MSCI-SADI and S&P-SADITR, which are more extreme than the t-statistic of alphas values from the bootstrap simulations of −1.94, −1.94 and −1.94, respectively. Therefore, even on considering Hypothesis 3.A on the opposite side of the cross-section of returns, to test whether significantly negative alphas can be attributed to a lack of stock-picking skills or persistent bad luck, the findings also fail to reject the null hypothesis, confirming that persistence in negative alphas are not due to bad luck. To illustrate, this result is confirmed in Figure 6.1, which shows that in the far-left tail, the t-statistic estimates of alphas from the actual estimates lie above that of the t-statistic of alphas from bootstrap simulations. Therefore, a few active mutual funds with underperforming returns also consistently underperform the market.

Table 6.7

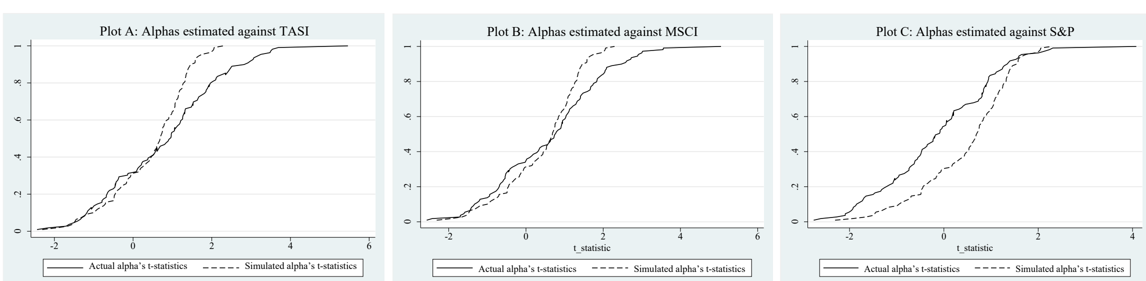
Percentiles of t-Statistic Estimates of Alphas for Actual and Simulated Fund Returns Using the FFC6FM Model Against TASI, MSCI-SADI and S&P-SADITR (January 2010 – December 2020)

Pct	*t*-statistic of Alphas TASI		*t*-statistic of Alphas MSCI-SADI		*t*-statistic of Alphas S&P-SADITR	
	Actual	Simulation	Actual	Simulation	Actual	Simulation
1%	-2.16	-1.94	-2.43	-1.94	-2.61	-1.94
5%	-1.41	-1.47	-1.58	-1.47	-2.01	-1.44
10%	-1.17	-0.99	-1.33	-0.99	-1.85	-0.95
20%	-0.66	-0.45	-0.69	-0.45	-1.21	-0.44
30%	-0.14	-0.06	-0.41	-0.06	-0.74	-0.021
40%	0.45	0.47	0.32	0.47	-0.47	0.52
Median	0.96	0.68	0.77	0.68	-0.09	0.7
60%	1.26	0.91	1.04	0.85	0.20	0.91
70%	1.63	1.09	1.41	1.08	0.79	1.09
80%	2.02	1.32	1.84	1.32	0.94	1.32
90%	2.92	1.57	2.58	1.57	1.37	1.57
95%	3.25	1.75	2.91	1.75	1.65	1.74
99%	3.69	2.06	3.56	2.06	2.31	2.05

Note. The table presents t-statistic estimates of alphas at selected percentiles (Pct) of the actual distribution of t-statistic estimates of alphas (Actual), and the corresponding mean t-statistic of alphas from bootstrap simulation (Simulation), respectively. The results are estimated based on FFC6FM against three different indices: TASI (in Columns 2 and 3, respectively), MSCI-SADI (in Columns 4 and 5, respectively) and S&P-SADITR (in Columns 6 and 7, respectively) from January 2010 to December 2020.

Figure 6.1

Actual and Simulated CDF of FFC6FM t-Statistic Estimates of Alphas for Net Returns (January 2010 – December 2020)



From these findings, one can conclude that fund managers with and without managerial skills coexist. The research indicates that active mutual funds with outperforming returns consistently outperform the market, whereas those with underperforming returns consistently lag behind the market. Notably, the results highlight that the prevalence of skilled managers is greater in Saudi Arabia than in developed markets. Specifically, the current findings reveal that skilled managers can be identified within the 80th percentile in Saudi Arabia, whereas in developed markets, their presence is confined maximum to the top 90th percentile (Cuthbertson et al., 2008; Kosowski et al., 2006). Jones and Wermers (2011) suggested that fierce competition among a large number of informed managers in developed markets drives fund performance towards zero. Consequently, a larger cohort of skilled managers may be evident in emerging markets than in developed markets. In essence, the current findings carry significant implications for market efficiency because the existence of mutual fund managers who can consistently beat the market over the long term implicitly challenges the assumptions of the EMH.

6.3.2.2 Bootstrap Analysis for the Period Before Financial Reforms (January 2010 to June 2015)

Table 6.8 presents the results of the actual alpha *t*-statistic estimates and of alpha *t*-statistics from bootstrap simulations from January 2010 to June 2015. On applying TASI and MSCI-SADI as proxies of market return for estimations, the results show that funds in the 40th percentile and above have actual alpha *t*-statistic estimates of 2.29 and 2.49, which are more than the corresponding estimates from bootstrap simulations of 1.68 and 1.68, respectively. Hypothesis 3.B of a positive true alpha, implying that positive alphas are a result of investment skills, is examined in contrast to the alternative hypothesis of a zero true alpha, assuming that all alphas produced are solely due to luck. The study fails to reject Hypothesis 3.B that mutual funds provide outperforming returns because of managers' stock-picking skills, confirming the existence of managerial skills among the top 40th percentile of fund performance in Saudi Arabia. However, on applying S&P-SADITR as the market return proxy to estimate alphas, the study finds that only funds in the top 70th percentile have managers who possess genuine stock-picking skills.

Figure 6.2 depicts the CDF of the cross-sectional distributions for both the actual and simulated t-statistic estimates of alphas. The study is interested in investigating the presence of funds with actual t-statistic estimates of alphas that exceed those corresponding estimates from the bootstrapped distribution. The results illustrated in Figure 6.2 confirm the observations from Table 6.8 that in the far-right tail, the t-statistic of alphas from bootstrap simulations lies below the actual t-statistic estimates of alphas in that region.

At the negative side of the performance scale, Table 6.8 shows that the left tail percentiles of actual alpha *t*-statistic estimates are far below the corresponding values from the bootstrap simulations. For instance, in the 1st percentile, the actual t-statistic estimates of alphas −2.47, −2.33 and −2.67 which were estimated against TASI, MSCI-SADI and S&P-SADITR, are below the t-statistic of alphas from the bootstrap simulations of −0.83, −0.83 and −0.83, respectively. On considering Hypothesis 3.B on the opposite side of the cross-section of returns, for testing whether significantly negative alphas can be attributed to poor stock-picking skills or persistent bad luck, these findings fail to reject the null hypothesis, confirming that persistence in negative alphas are not due to bad luck. Figure 6.2 also shows that in the far-left tail, the t-statistic of alphas from bootstrap simulations lies below that of actual t-statistic estimates of alphas in that region. Last, active mutual funds with underperforming returns persistently underperform the market.

Table 6.8

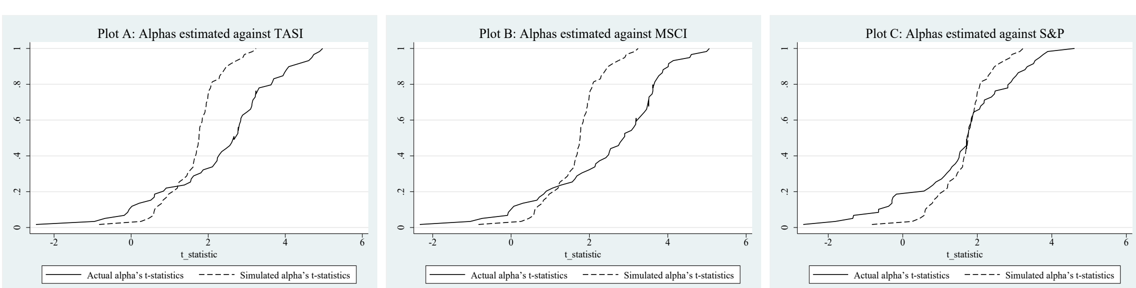
Percentiles of t-Statistic Estimates of Alphas for Actual and Simulated Fund Returns Using the FFC6FM Model Against TASI, MSCI-SADI, and S&P-SADITR (January 2010 – June 2015)

Pct	*t*-statistic of Alphas TASI		*t*-statistic of Alphas MSCI-SADI		*t*-statistic of Alphas S&P-SADITR	
	Actual	Simulation	Actual	Simulation	Actual	Simulation
1%	-2.47	-0.83	-2.33	-0.83	-2.67	-0.83
5%	-0.68	0.46	-0.74	0.46	-1.34	0.45
10%	-0.05	0.61	0.00	0.61	-0.65	0.61
20%	0.84	1.10	0.9	1.10	0.57	1.09
30%	1.81	1.47	1.81	1.47	1.19	1.47
40%	2.29	1.68	2.49	1.68	1.52	1.68
Median	2.67	1.76	2.9	1.76	1.73	1.76
60%	2.85	1.85	3.19	1.85	1.85	1.85
70%	3.16	1.98	3.51	1.99	2.19	1.98
80%	3.67	2.10	3.67	2.11	2.91	2.1
90%	4.35	2.59	4.02	2.59	3.51	2.58
95%	4.74	2.94	4.60	2.94	3.77	2.93
99%	4.97	3.24	5.06	3.24	4.61	3.22

Note. The table presents t-statistic estimates of alphas at selected percentiles (Pct) of the actual distribution of t-statistic estimates of alphas (Actual), and the corresponding mean t-statistic of alphas from bootstrap simulation (Simulation), respectively. The results are estimated based on FFC6FM against three different indices: TASI (in Columns 2 and 3, respectively), MSCI-SADI (in Columns 4 and 5, respectively) and S&P-SADITR (in Columns 6 and 7, respectively) for the January 2010 – June 2015 period.

Figure 6.2

Actual and Simulated CDF of FFC6FM t-Statistic Estimates of Alphas for Net Returns (January 2010 – June 2015)



6.3.2.3 Bootstrap Analysis for the Period After the Financial Reforms (July 2015 – December 2020)

Table 6.9 presents the results of actual alpha *t*-statistic estimates and of the alpha *t*-statistic from bootstrap simulations for July 2015 to December 2020. The results show that regardless of the index applied as the market return proxy in the estimations, only funds in the 99th percentile and above produce actual alpha *t*-statistic estimates of 3.16, 2.71 and 2.13 that are above the corresponding alpha *t*-statistic from bootstrap simulations of 2.08, 2.08 and 2.08, respectively. Hypothesis 3.C of a positive true alpha, implying that positive alphas are a result of managerial skills, is examined in contrast to the alternative hypothesis of a zero true alpha, assuming that all alphas produced are solely due to luck. Therefore, the study fails to reject Hypothesis 3.C that mutual funds outperform the market because of real managerial skills as the actual alpha *t*-statistic estimates are above the corresponding alpha *t*-statistic from bootstrap simulations, confirming the existence of managers' stock-picking skills only among the top 99th percentile of funds in Saudi Arabia. Figure 6.3 depicts the CDF of the cross-sectional distributions for both the actual and simulated t-statistic estimates of alphas. The study's interest lies in investigating the existence of funds with actual t-statistic estimates of alphas that exceed a certain level of the corresponding t-statistic of alphas from the bootstrapped simulations. The results depicted in Figure 6.3 confirm the observations from Table 6.9 that in the far-right tail, the t-statistic of alphas from bootstrap simulations lies below actual t-statistic estimates of alphas to the left in that region. Overall, the findings suggest there is obvious scarcity of persistent outperforming returns among individual mutual funds during the subsample period after financial reforms.

Table 6.9 shows that the left tail percentiles of the alpha *t*-statistics of actual estimates are lower than the corresponding values from the bootstrap simulations. In the 1st percentile, the actual t-statistic estimates of alphas of −2.47, −2.69 and −2.99 which were estimated against TASI, MSCI-SADI and S&P-SADITR, are more extreme than the t-statistic of alphas from the bootstrap simulations of −2.28, −2.28 and 2.27, respectively. On considering Hypothesis 3.C on the opposite side of the cross-section of returns, for testing whether significantly negative alphas are result of inferior stock-picking skills or persistent bad luck, these results fail to reject the null hypothesis, indicating that persistence in negative alphas is not due to bad luck. Figure 6.3 depicts the CDF of the cross-sectional distributions for both the actual t-statistic estimates of alphas and those from bootstrap simulations. In the figure, at the far-left tail, the actual t-statistic estimates of alphas lie at the extreme left to that of the *t*-statistic from bootstrap simulations, confirming that persistence in negative alphas is not due to bad luck; rather, funds with underperforming returns persistently underperform the market.

Table 6.9

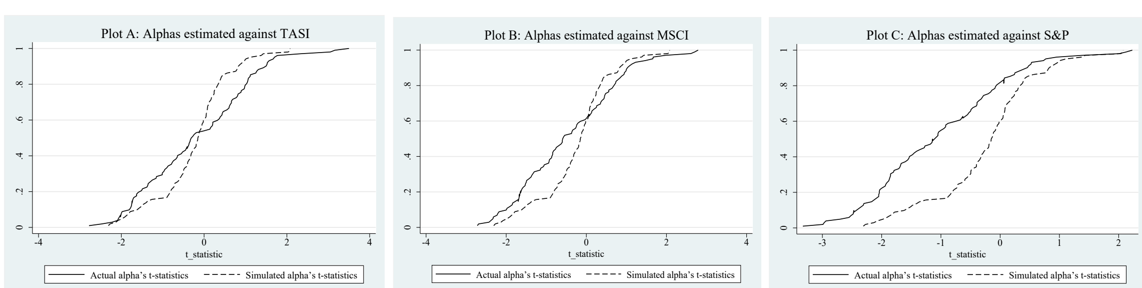
Percentiles of t-Statistic Estimates of Alphas for Actual and Simulated Fund Returns Using the FFC6FM Model Against TASI, MSCI-SADI and S&P-SADITR (July 2015 – December 2020)

Pct	*t*-statistic of Alphas TASI		*t*-statistic of Alphas MSCI-SADI		*t*-statistic of Alphas S&P-SADITR	
	Actual	Simulation	Actual	Simulation	Actual	Simulation
1%	-2.47	-2.28	-2.69	-2.28	-2.99	-2.27
5%	-2.02	-1.91	-2.32	-1.91	-2.55	-1.91
10%	-1.78	-1.57	-1.98	-1.57	-2.39	-1.57
20%	-1.51	-0.80	-1.64	-0.80	-2.04	-0.80
30%	-1.01	-0.50	-1.33	-0.50	-1.85	-0.50
40%	-0.64	-0.31	-0.86	-0.32	-1.53	-0.32
Median	-0.29	-0.14	-0.58	-0.14	-1.11	-0.14
60%	0.37	0.02	-0.03	0.02	-0.67	0.02
70%	0.66	0.14	0.36	0.14	-0.39	0.14
80%	1.03	0.35	0.70	0.35	-0.06	0.35
90%	1.50	0.83	1.03	0.83	0.46	0.83
95%	1.70	1.11	1.66	1.11	0.77	1.11
99%	3.16	2.08	2.71	2.08	2.13	2.08

Note. The table presents t-statistic estimates of alphas at selected percentiles (Pct) of the actual distribution of t-statistic estimates of alphas (Actual), and the corresponding t-statistic of alphas from bootstrap simulation (Simulation), respectively. The results are estimated based on FFC6FM against three different indices TASI (in Columns 2 and 3, respectively), MSCI-SADI (in Columns 4 and 5, respectively) and S&P-SADITR (in Columns 6 and 7, respectively) for the July 2015 – December 2020 period.

Figure 6.3

Actual and Simulated CDF of FFC6FM t-Statistic Estimates of Alphas for Net Returns (July 2015 – December 2020)



6.3.2.4 Comparison Between the Results of Bootstrap Analysis for the Pre- and Post-Reform Periods

By comparing mutual fund performance persistence for the periods before and after financial reforms, this study shows that outperforming fund managers have become scarcer since July 2015. The data presented in Tables 6.5 and 6.6 demonstrate a significant decline in the number of mutual funds that exhibit persistence in outperforming returns. Prior to the financial reforms, these funds could be found in the 40th percentile and above, whereas post reforms, they are exclusively found within the top 99th percentile. The current results of the subsample analysis are consistent with those of Kosowski et al. (2006), who also divided their sample into two subsamples: one for 1975–1989, and the other for 1990–2002. They found that outperforming fund managers have become scarce since 1990 in the US. They suggested that the decrease in the number of outperforming fund managers could be attributed to either an increase in market efficiency, or the fierce competition among the large number of new funds or perhaps these two reasons are related.

Several factors could explain the reduction in the number of outperforming funds in Saudi Arabia following the 2015 financial reforms. One significant contributing factor appears to be the liberalisation of the Saudi stock market in 2015. This move brought about the entry of QFIIs into the Saudi Arabian equity market, which subsequently reduced speculative activities by local individual traders. Consequently, this reduction in speculative trading has limited the occurrence of mispriced opportunities within this market. According to the monthly trading and ownership reports provided by Tadawul (2020), the monthly average trading volume by individual traders, as a percentage of the total trading volume, witnessed a notable decline. Specifically, it decreased from a substantial 91% over the five-year period preceding July 2015 to 73% during the five-year period following July 2015.[41] These data support the argument that the liberalisation in 2015 had a tangible impact on market dynamics. Further corroboration of these changes is provided by Sharif (2019), who affirmed that this liberalisation led to improvements in various aspects of the market, including the stock price discovery process (valuation), the narrowing of ask–bid spreads (liquidity) and a reduction in high–low price volatility.

Another possible explanation for the decline in the number of outperforming funds could be the substantial decrease in the count of equity funds. Specifically, the number of equity funds in Saudi Arabia decreased from 169 funds with total assets of USD8,803 million in 2015 to 128 funds with assets amounting to USD5,659 million by 2020 (for further details of this trend, see Chapter 2). Notably, underperforming funds rather than outperforming funds typically tend to exit the market, as suggested by Malkiel (1995).

6.4 Chapter Summary

In this chapter, the study explored the individual performance of mutual funds by examining the existence of managerial skills among a group of active mutual funds in Saudi Arabia. In funds' aggregate performance results, those with significantly positive alphas could be balanced by funds with significantly negative alphas. The challenge here is to separate skills from luck for those funds with significant alphas. A conventional approach to tackle this issue is to test for persistence in active mutual fund return performance, that is, whether outperforming funds continue to outperform and underperforming funds continue to underperform. There are several approaches to test for persistence in active mutual fund return performance (see, e.g. Grinblatt & Titman, 1992; Hendricks et al., 1993). However, given the potential non-normality in the

[41] The reports by Tadawul (2020) provide only the trading volume as the number for each category of investors. Therefore, the researcher calculated the average trading volume by individual traders as the percentage of total trading volume for the two sample periods.

distributions of individual fund alphas, the bootstrap statistical technique stands out among the other methods because it addresses this issue (Kosowski et al., 2006).

The bootstrap statistical technique compares the actual cross-section of t-statistic estimates of funds' alphas to the results from bootstrap simulations of the cross-section that emulates the properties of actual fund alphas. If the right tail of the actual cross-section of t-statistic estimates of funds' alphas exceeds the corresponding t-statistic of alphas from the bootstrapped simulations, then luck is not the sole source of significant mutual fund performance and fund managers with stock-picking skills do exist. The findings of the current empirical analysis provide valuable insights into the relationship between fund performance and managerial skills, particularly in the context of Saudi Arabia. The study also divided the analysis into two subsample periods: the periods before and after the financial reforms of 2015.

During the overall sample period (January 2010 – December 2020), the study observed that the right tail of the actual cross-section of t-statistic estimates of funds' alphas exceeded that from the bootstrapped simulations, indicating persistence in fund outperformance. In detail, the findings confirm the existence of fund managers with stock-picking skills among the top 80th percentile of funds in Saudi Arabia. However, when using S&P-SADITR as the market return proxy, the study found evidence that only funds in the top 99th percentile possessed genuine stock-picking skills. Hence, it is evident that only a very small number of fund managers can consistently outperform the market when fund performance is measured by using S&P-SADITR, in contrast to when it is evaluated by using TASI and MSCI-SADI. This difference arises because S&P-SADITR incorporates accumulated dividends from its constituents in its overall returns.

Overall, the current findings suggest that a certain group of skilled managers in Saudi Arabia have sufficient talent for stock selection, supporting the hypothesis that investment skills do exist. The current findings differ from those of prior studies that did not find evidence of skilled managers and from those studies that found evidence of skilled managers only among a limited group of funds (Fama & French, 2010; Tapver, 2023; Yang & Liu, 2017), emphasising the uniqueness of the Saudi Arabian market. In contrast, active mutual funds with underperforming returns persistently underperformed the market. This persistence in negative alphas implies that these funds lacked stock-picking skills, rather than this underperformance being a result of bad luck. The results indicate that the left tail percentiles of actual t-statistic estimates of alphas exceeded those from bootstrap simulations, further supporting the conclusion that underperforming funds also exhibit persistence in performance. In sum, the findings of this study imply that outperforming and underperforming returns can be attributed to the stock-picking skills of fund managers.

To explore whether the cross-sectional distribution of mutual fund performance changes over the overall sample period, this study examined two subsample periods: those before the 2015 financial reforms (January 2010 – June 2015) and after it (July 2015 – December 2020). This analysis showed contrasting results. First, by examining the existence of stock-picking skills of fund managers for the pre-reform period, the study observed remarkable outperforming returns persistence among active mutual funds, confirming the existence of stock-picking skills among fund managers. Funds in the top 40th percentile and above consistently outperformed the market, indicating the existence of such skills among this group. Similarly, the study found evidence that only funds in the top 70th percentile possessed genuine stock-picking skills when using S&P-SADITR as the proxy of market returns. In contrast, in the post-reform period, there was a scarcity of superior performance persistence among active mutual funds. Only funds in the top 99th percentile and above produced t-statistic estimates of alphas that exceed those from bootstrap simulations. This finding suggests a significant decline in the number of mutual funds exhibiting persistent outperforming returns since the implementation of financial reforms in Saudi Arabia.

Further, a comparison of the results for the subsample periods showed that outperforming fund managers have become scarcer since the financial reforms in July 2015. Prior to the reforms, funds with persistent superior performance could be found in the 40^{th} percentile and above, whereas post reforms, they were exclusively found within the top 99^{th} percentile. This trend aligns with the findings of prior studies about a decline in the number of outperforming fund managers in developed markets (Kosowski et al., 2006), possibly due to increased market efficiency or fierce competition among funds.

Chapter 7: Impact of Investor Sentiment on Mutual Funds Performance

7.1 Introduction

The preceding two chapters examined Hypotheses 2 and 3, focusing on the aggregate and individual performance of mutual funds, respectively. This chapter examines Hypothesis 4, emphasising the potential factors influencing mutual fund performance. This research builds upon the existing body of literature that has explored factors influencing mutual fund performance (Alsubaiei et al., 2024; Carhart, 1997; Ferreira et al., 2013; G. Jiang & Yuksel, 2017; Mansor et al., 2015; Merdad et al., 2016; Yan, 2008). It expands this literature by investigating the potential influence of investor sentiment, as a new factor, and re-examining the impact of oil price volatility on mutual fund performance, along with fund-specific factors, such as compliance with Islamic law, management expense ratios, fund flows, fund age and fund size. This introduction provides an overview of the chapter's content, setting the stage for the subsequent discussion. It briefly reviews the research context, objectives, contribution and significance, and the structure of the chapter.

This chapter aims to explore the influence of investor sentiment on the performance of both active and passive mutual funds, considering the pivotal role that investor sentiment plays in the equity market of Saudi Arabia. One of the most distinctive characteristics of this market is the dominant presence of individual traders. According to monthly trading and ownership reports from Tadawul (2020), the monthly average trading volume percentage of individual traders was 82% in 2010–2020, which is significantly higher than the corresponding percentage for developed markets. Investor sentiment is widely used to measure the noisy expectations of individual traders through a range of proxies, and the influence of investor sentiment on equity markets is well established in the finance literature (e.g. Baker & Wurgler, 2007; Barber et al., 2009; DeLong et al., 1990; Kumar & Lee, 2006; W. Lee et al., 2002). However, investor sentiment plays an even more significant role in the Saudi Arabian equity market owing to the substantial presence of individual traders. For example, Altuwaijri (2016) and Alnafea and Chebbi (2022) showed that investor sentiment influences the returns and volatility, respectively of this market.

However, as demonstrated in the previous two chapters, mutual fund performance may vary from the overall market portfolio because of the funds' professional managers (i.e. while mutual funds exclusively hold stocks from the market, the distinct weights assigned to these stocks in their portfolios contribute to variations in returns compared with the overall market). On one hand, the expertise of fund managers plays a decisive role in determining mutual fund performance. On the other hand, the excessive involvement of individual traders in trading within the Saudi market and their ability to influence market returns and volatility may establish a relationship between investor sentiment and fund performance. To the best of this researcher's understanding, to date, no study has specifically examined the influence of investor sentiment on mutual fund performance. Hence, this study will bridge this knowledge gap by examining the potential influence of investor sentiment on mutual fund performance. To this end, the study applies five proxies for investor sentiment: trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA, on two measures of mutual fund return performance (unadjusted return performance and risk-adjusted return performance).

This study on the influence of investor sentiment on mutual fund performance is vital for various reasons, particularly in the context of the Saudi Arabian market, which is highly dominated by individual investors. First, it identifies the relationship between investor sentiment and mutual fund performance, revealing the extent to which both fund unadjusted and risk-adjusted performance are driven by investor sentiment. Second, finding such a relationship allows investors to identify the funds that are highly sensitive to investor sentiment (significantly outperforming the market when sentiment is high and significantly underperforming when sentiment is low), enabling wise investors to time their investment decisions in funds according to investor sentiment. Last, such a study can have broader policy implications. Regulators and policymakers can use the findings to develop appropriate regulations, investor protection measures and market surveillance mechanisms to ensure the stability and integrity of the financial system.

The next section provides descriptive statistics, offering an initial exploration of the data. It establishes a foundation for the subsequent analysis and provides initial insights into the research topic. This section helps to understand the data characteristics and identify potential patterns or relationships, and it sets the stage for more in-depth analysis and interpretation in later sections of this chapter. In Section 7.3, the study first examines the hypotheses and presents the empirical findings derived from the analysis. Then, it analyses and explains the meaning of the results, addressing any unexpected or significant findings, and interprets the empirical findings while discussing their implications in relation to the research objectives. Last, Section 7.4 summarises the chapter.

7.2 Summary Statistics of Main Variables

This chapter conducts a descriptive statistical analysis of dependent variables as well as independent variables. To ensure an unbiased sample, the fund data considered encompass both existing and liquidated funds, thus eliminating any potential survivorship bias. In this section, the study maintains a stringent criterion by restricting the sample to funds with a minimum operating period of 12 months. This approach guarantees that none of the 120 active funds and 14 passive funds were excluded from the analysis. This section provides an overview of the key variables that will be analysed in this chapter and describes their main characteristics. The review of both dependent and independent variables helps in understanding the range and variability of the data.

Tables 7.1 and 7.2 present the descriptive statistics for the dependent variables: the unadjusted return and risk-adjusted returns of active and passive mutual funds, respectively. On average, active and passive mutual funds during the current study period (from January 2010 to December 2020) had monthly unadjusted returns of 0.32% and 0.30%, respectively, with corresponding standard deviations of 6.7% and 5.5%, respectively. After return adjustments on TASI, MSCI-SADI and S&P-SADITR,[42] active funds generated risk-adjusted return performance of 0.17%, 0.135% and −0.032%, respectively, with standard deviations ranging around 2.4%. In contrast, passive funds produced −0.007%, −0.03% and −0.24%, respectively, with standard deviations ranging between 2.5% and 2.6%. These statistics shed light on the performance characteristics of both types of mutual funds and provide valuable insights into their return patterns and risk profiles.

Moderate correlations have been observed between the unadjusted returns and risk-adjusted returns for active and passive funds, typically falling within the ranges of 36–37% and 45–47%, respectively. Notably, the correlations among risk-adjusted returns, calculated using different indices, are remarkably strong. For active funds, these correlations range from 94% to 99%, and for passive funds, from 93% to 98%. These robust correlations should not pose a concern, as the tested factors will be regressed on each of them separately.

[42] The FFC6FM is used to estimate the risk-adjusted return performance, and three indices (TASI, MSCI-SADI, and S&P-SADITR) are used as the market return proxies.

Table 7.1

Summary Statistics of Active Fund Unadjusted Returns and Risk-Adjusted Returns Against Benchmark Indices (Dependent Variables), January 2010 – December 2020

Variable	*Mean* %	*SD* %	Correlations %			
			(1)	(2)	(3)	(4)
1. Unadjusted return	0.3179	6.705	100			
2. Risk-adjusted returns: TASI	0.1748	2.456	36.73	100		
3. Risk-adjusted returns: MSCI-SADI	0.1357	2.471	37.39	94.72	100	
4. Risk-adjusted returns: S&P-SADITR	-0.0325	2.447	36.53	99.15	94.7	100

Note. This table presents the unadjusted returns of active funds. Moreover, it presents the risk-adjusted returns; the FFC6FM is used to estimate the risk-adjusted performance against three indices: TASI, MSCI-SADI and S&P-SADITR. The table also reports the standard deviations for those variables and the correlations between them.

Table 7.2

Summary Statistics of Passive Fund Unadjusted Returns and Risk-Adjusted Returns Against Benchmark Indices (Dependent Variables), January 2010 – December 2020

Variable	*Mean* %	*SD* %	Correlations %			
			(1)	(2)	(3)	(4)
1. Unadjusted return	0.3035	5.49	100			
2. Risk-adjusted returns: TASI	-0.0073	2.58	47.15	100		
3. Risk-adjusted returns: MSCI-SADI	-0.0320	2.60	47.44	93.56	100	
4. Risk-adjusted returns: S&P-SADITR	-0.2410	2.51	45.89	98.88	93.47	100

Note. This table presents the unadjusted returns of passive funds. Moreover, it presents the risk-adjusted returns; the SFM is used to estimate the risk-adjusted performance against three indices: TASI, MSCI-SADI and S&P-SADITR. The table also reports the standard deviations for those variables and the correlations between them.

Table 7.3 presents the descriptive statistics for the independent variables. This study focuses on the potential influence of investor sentiment on mutual fund performance. As explained in the literature review in Chapter 3, prior studies applied various proxies for investor sentiment. However, this study applies five proxies of investor sentiment: market trading volume, market turnover ratio, average P/E ratio, bull–bear ratio and the IPCSI-SA (Section 4.7.1 explained how these proxies represent investor sentiment). The first proxy, market trading volume, is the total monthly number of shares traded (transformed into natural logarithm). The results reveal an average market trading volume of 21.8, with a standard deviation of 0.59, illustrating the level of engagement and interest among investors. Next, the market turnover ratio represents the liquidity of the Saudi Arabian market. By dividing the total traded value on the market's capitalisation (i.e. free-float capitalisation is used in this study), this proxy provides insights into the pace and frequency of market transactions. In this study, the market turnover ratio yields an average of 0.12, with a standard deviation of 0.071.

The third proxy is the average P/E ratio. A higher P/E ratio implies more optimistic sentiment, and the study reports an average value of 0.005, accompanied by a standard deviation of 0.17, revealing the prevailing sentiments surrounding stock valuations. As investor sentiment can sway between bullish and bearish tendencies, the fourth proxy, the bull–bear ratio, comes into play. This sentiment indicator measures the ratio of rising stocks (bullish sentiment) to those of falling stocks (bearish sentiment) in the market. The findings show an average bull–bear ratio of −0.041, with a standard deviation of 1.64. Last, the IPCSI-SA represents a comprehensive measure of investor sentiment, capturing multiple aspects of investor perception and confidence in the Saudi Arabian market. With an average value of 0.00024 and a standard deviation of 0.042, this index provides valuable insights into investor sentiment.

The other independent variables in Table 7.3 include the oil price realised volatility, fund flows, management expense ratio, fund age, fund size and compliance with Islamic law. The first variable, oil price realised volatility, examines the fluctuations and uncertainty in oil prices in the world-largest exporter country. With an average value of 0.021 and a standard deviation of 0.0178, this variable provides crucial information about the significant impact of oil prices on investment decisions. The second, the fund flows variable, serves as a vital indicator of the capital movement in and out of funds. The average net fund flow is 0.0711, along with a standard deviation of 3.28.

This variable sheds light on investor preferences and its potential impact on mutual fund performance. The third, the management expense ratio, measures the cost of managing funds for investors. With an average value of 0.0381 and a standard deviation of 0.0094, this variable plays a significant role in gauging the impact of fees on mutual fund performance, making it an essential aspect of the overall analysis.

The fourth variable, the fund age measured in years, emerges as another influential variable in this study. With an average value of 95.53 and a standard deviation of 78.31, this variable provides essential information on the maturity and experience of funds. This, in turn, helps understand the potential link between the age of the funds and mutual fund performance. The fifth variable, fund size, expressed as the natural logarithm of total net asset, plays a pivotal role in understanding the scale and magnitude of funds in the market. With an average value of 17.93, along with a standard deviation of 1.85, this variable sheds light on the distribution of funds of varying sizes and their potential influence on mutual fund performance. The last, the compliance with Islamic law variable, as a categorical factor, carries immense significance in the context of the Saudi Arabian market, where Islamic finance principles are upheld. With an average value of 0.7151, denoting the proportion of funds compliant with Islamic law, and a standard deviation of 0.4513, this variable provides valuable insights into the potential influence of adhering to Islamic law on mutual fund performance. In addition, the pairwise correlations between these independent variables show non-significant relationships between them, which minimises any potential multicollinearity in the models.

Table 7.3

Summary Statistics of Independent Variables Included in the Study (January 2010 – December 2020)

Variable	*M%*	*SD%*	Correlations										
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1. Market trading volume	21.84	0.5915	1.00										
2. Market turnover ratio	0.124	0.0717	0.8789	1.00									
3. Average P/E ratio	0.005	0.1768	0.0635	0.1022	1.00								
4. Bull–bear ratio	-0.041	1.6404	0.2301	0.1899	-0.1728	1.00							
5. IPCSI-SA	0.0002	0.0429	0.0215	0.0461	0.0171	0.0468	1.00						
6. Oil price realised volatility	0.021	0.0179	0.0780	-0.0076	-0.0356	0.1546	-0.0983	1.00					
7. Compliance with Islamic law	0.715	0.4513	-0.0144	-0.0257	-0.0268	0.0037	-0.0030	0.0091	1.00				
8. Management expense ratio	0.038	0.0094	-0.0058	-0.0010	0.0196	0.0049	0.0015	0.0100	-0.039	1.00			
9. Fund net flow	0.071	3.2859	-0.0045	-0.0055	0.0038	-0.0043	0.0014	-0.0049	-0.014	0.0189	1.00		
10. Fund age (in years)	95.53	78.310	-0.0264	-0.0252	0.0581	0.0169	0.0027	0.0449	-0.215	0.0761	-0.025	1.00	
11. Total net assets	17.94	1.8541	0.0923	0.0999	0.0407	-0.0120	0.0012	-0.0438	-0.059	0.0710	-0.021	0.483	1.00

7.3 Estimations of Panel Data Regressions

This section considers panel data regressions to address the impact of investor sentiment, as a new factor, and fund-specific factors, on mutual fund performance. The dependent variables encompass the unadjusted return performance, which is measured using Equation (1) in Chapter 4 for each fund, and risk-adjusted return performance, which is estimated using Equation (8) in Chapter 4 for each fund among both active and passive mutual funds. The independent variables include a range of factors, such as investor sentiment (proxied by market trading volume, market turnover ratio, average P/E ratio, bull–bear ratio and IPCSI-SA), oil price realised volatility, fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. The study has demonstrated how each factor is measured in Chapter 4.

The common procedures for model selection tests, which were demonstrated in Chapter 4 to determine the appropriate model specification for panel data analysis, have identified the pooled OLS regression model as suitable. Subsequently, Equation (25) in Chapter 4 was estimated using univariate pooled OLS regressions to assess the impact of each investor sentiment proxy on mutual fund performance individually. Then, multivariate pooled OLS regressions were conducted, incorporating other independent variables into previous estimations. This comprehensive analysis aimed to measure the combined influence of investor sentiment and fund-specific factors on both active and passive fund performance in Saudi Arabia. Last, a simple comparison will be used in this section to identify the difference in the impact on active and passive funds. Sections 7.3.1 and 7.3.2 explore the influence on unadjusted return performance, while Sections 7.3.3 and 7.3.4 focuses on the influence on risk-adjusted return performance.

7.3.1 Measuring the Impact of Investor Sentiment on Unadjusted Returns

Table 7.4 and Table 7.5 present the results of pooled OLS regressions investigating the unadjusted returns of active and passive mutual funds based on various factors, including investor sentiment, oil price volatility, fund net flow, management expense ratio, fund age, compliance with Islamic law and fund size. However, this section considers only the univariate pooled OLS regressions in Models 1, 3, 5, 7 and 9 that examined the impact of each proxy of investor sentiment independently, namely trading volume (in Model 1), market turnover (in Model 3), average P/E ratio (in Model 5), bull–bear ratio (in Model 7) and IPCSI-SA (in Model 9), on the unadjusted return performance of active and passive mutual funds. The results for active funds are discussed in Subsection 7.3.1.1, whereas those for passive funds are discussed in Subsection 7.3.1.2.

7.3.1.1 Impact of Investor Sentiment on Unadjusted Returns of Active Funds

The results in Models 1, 3, 5, 7 and 9 in Table 7.4 are the outcome of univariate pooled OLS regressions of only investor sentiment on the unadjusted returns of active funds. The results show that all proxies of investor sentiment have a positive impact on such returns. First, the coefficient of 0.014 for trading volume implies that for every 1% increase in trading volume, the unadjusted return of active mutual funds increases by 0.014% and it is statistically significant at the 1% level. A higher trading volume leads to higher unadjusted returns for active mutual funds. Second, the coefficient of 0.135 for the market turnover ratio suggests that a 1% increase in the turnover ratio corresponds to a 0.135% increase in the unadjusted return performance of active mutual funds. This result also holds statistical significance at the 1% level. A higher turnover ratio signifies increased trading activities and potentially heightened market sentiment, which could contribute to increased fund returns. Third, the coefficient of 0.019 for the P/E ratio implies that for every 1% increase in the P/E ratio, the unadjusted returns of active mutual funds rise by

0.019%. With a statistically significant relationship at the 1% level, this finding suggests that elevated P/E ratios may signal optimistic investor sentiment, leading to higher returns for active funds. Fourth, the coefficient of 0.026 for the bull–bear ratio indicates that a 1% increase in the ratio corresponds to a 0.026% increase in the unadjusted return of active mutual funds. The statistical significance at the 1% level supports the notion that a higher bull–bear ratio, indicating bullish sentiment, may positively influence active fund returns. Fifth, the coefficient of 0.062 for the IPCSI-SA implies that a 1% increase in the index is associated with a 0.062% increase in the unadjusted return performance of active mutual funds. The strong statistical significance at the 1% level reinforces the influence of investor sentiment, as measured by the IPCSI-SA.

7.3.1.2 Impact of Investor Sentiment on Unadjusted Returns of Passive Funds

The outcomes presented in Models 1, 3, 5, 7 and 9 in Table 7.5 were derived from univariate pooled OLS regressions. These regressions specifically explore the impact of investor sentiment on the unadjusted returns of passive funds. The findings show that most proxies of investor sentiment have a positive impact on these returns. The coefficient of 0.015 for trading volume suggests that for every one-unit increase in trading volume, the unadjusted returns of passive mutual funds increase by 0.015%. The statistical significance at the 1% level indicates that higher trading activity, potentially influenced by investor sentiment, contributes to increased returns for passive funds. Further, the coefficient of 0.128 for the market turnover ratio indicates that a 1% increase in the market turnover ratio corresponds to a 0.128% increase in the unadjusted return performance of passive funds. Similarly to the results for active funds, the significance at the 1% level suggests that sentiment-induced market turnover plays a role in driving the performance of passive funds as well. This implies that increased trading activity driven by investor sentiment might have positive effects on the unadjusted returns of both types of mutual funds. Moreover, the coefficient for the bull–bear ratio indicates that a 1% increase in the ratio corresponds to a 0.027% increase in the unadjusted return performance of passive mutual funds. Importantly, this relationship is statistically significant at the 1% level, underscoring the role of the bull–bear ratio as a predictor of passive fund returns. The bull–bear ratio, which reflects the relative strength of bullish versus bearish sentiment in the market, appears to have a consistent influence on passive fund performance. However, the coefficients for both the P/E Ratio and IPCSI-SA show no statistical significance, suggesting they may not significantly affect the unadjusted return performance of passive funds in this study.

To the best of this researcher's knowledge, this is the first study that identifies the relationship between investor sentiment and the unadjusted return performance of mutual funds. Overall, this study finds that investor sentiment has a positive and significant impact on the unadjusted return performance of active and passive mutual funds, suggesting that investor sentiment plays a significant role in influencing the unadjusted return performance of both types of funds. These findings are in line with those of past studies demonstrating a positive influence of investor sentiment on the returns and volatility of the main stock market of Saudi Arabia (Alnafea & Chebbi, 2022; Altuwaijri, 2016). Considering the findings in Tables 7.4 and 7.5, the study fails to reject Hypothesis 4.A for both active and passive mutual funds. These findings reveal the extent to which the unadjusted returns of active and passive funds are driven by investor sentiment and provide an understanding of market dynamics.

7.3.2 Measuring the Impact of Investor Sentiment and Fund-Specific Factors on Unadjusted Returns

After examining the impact of each proxy of investor sentiment independently through univariate pooled regressions in the preceding Section 7.3.1, this section turns to the results of multivariate pooled OLS regressions in Models 2, 4, 6, 8 and 10 in Table 7.4 and Table 7.5. In addition to incorporating investor sentiment, these models incorporate oil price volatility and the following fund-specific factors: fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. The focus is on understanding their combined effects on the unadjusted returns of active and passive funds. The results for active funds are discussed in Subsection 7.3.2.1, while those for passive funds are discussed in Subsection 7.3.2.2.

7.3.2.1 Impact of Investor Sentiment and Fund-Specific Factors on Unadjusted Returns of Active Funds

The results of the multivariate pooled OLS regressions in Models 2, 4, 6, 8 and 10 in Table 7.4 incorporate the effects of the variables of oil price volatility and fund-specific factors, in addition to investor sentiment, on the unadjusted returns of active funds. Overall, Models 2, 4, 6, 8 and 10 consistently demonstrate higher explanatory power in capturing the variations in these returns. The results confirm that the unadjusted returns of active funds are significantly and positively responsive to investor sentiment. These findings are strongly consistent with the findings of the univariate pooled OLS regressions for all proxies of investor sentiment.

Moreover, the findings demonstrate that oil price volatility, management expense ratio and fund age have a significant impact on the unadjusted return performance of active mutual funds. The coefficient of −0.37 suggests that a 1% increase in oil price volatility corresponds to a 0.37% decrease in the unadjusted return performance of active mutual funds. The statistical significance at the 1% level indicates that oil price volatility has a remarkable negative impact on fund returns. These findings align with those of prior studies that have demonstrated the transmission of volatilities between oil prices and the Saudi Arabian equity market (Almohaimeed & Harrathi, 2013; Arouri et al., 2011). In addition, it corroborates Alsubaiei et al.'s (2024) findings that highlight the negative significant impact of oil market volatility on mutual fund unadjusted returns. The findings of the current study assert that higher volatility in oil prices can create market uncertainties and negatively affect the performance of funds. Based on these results, the study fails to reject Hypothesis 4.C that assumes a negative impact of oil price volatility on active fund unadjusted return performance.

The management expense ratio has a coefficient of 0.15, which implies that a 1% increase in this ratio results in a 0.15% increase in the unadjusted return performance of active mutual funds. The findings show that there is a significant relationship at the 1% level, suggesting an association between higher expense ratios and improvement in the unadjusted returns of funds. Although several studies found a negative relationship between expense ratio and fund returns, including those of Ferreira et al. (2013) and Mansor et al. (2015), the findings of this study reinforce the results of other studies, such as those of Díaz-Mendoza et al. (2014) and Droms and Walker (1996), which found a positive relationship between the expense ratio and fund returns. The positive relationship observed can be attributed to the fact that funds with higher unadjusted returns tend to charge higher management fees. For active mutual funds, these results reject Hypothesis 4.G of negative impact and prove there is a statistically significant positive impact.

The coefficient of fund age is 0.0033 and indicates that a one-month increase in fund age corresponds to a 0.0033% increase in the unadjusted return performance of active mutual funds. The statistical significance at the 1% level suggests that older funds tend to have slightly higher unadjusted returns. However, this study's empirical results on Saudi Arabian active mutual funds contrasts with those of most studies on developed markets that found no influence of fund age on mutual fund performance (Ferreira et al., 2013; Lou, 2012; Pollet & Wilson, 2008; Tang et al., 2012; Yan, 2008). Therefore, the current empirical results fail to reject Hypothesis 4.I that there is an impact of fund age on active mutual fund unadjusted return performance. It is essential to highlight that the study did not discover sufficient evidence to support the impact of fund flow, compliance with Islamic law and fund size on the unadjusted return performance of active funds. Hence, Hypotheses 4.E, 4.K and 4.M are hereby rejected for active funds.

7.3.2.2 Impact of Investor Sentiment and Fund-Specific Factors on Unadjusted Returns of Passive Funds

In addition to the impact of investor sentiment, the multivariate pooled OLS regressions in Models 2, 4, 6, 8 and 10 in Table 7.5 examine the influence of oil price volatility and fund-specific factors on the unadjusted returns of passive mutual funds. In general, Models 2, 4 and 8 have provided better explanations of the variations in the unadjusted returns of passive funds. The results indicate a significant and positive relationship between passive mutual fund returns and three key proxies of investor sentiment: the trading volume, market turnover and bull–bear ratio. These findings align closely with the results obtained from the univariate pooled OLS regressions for the three proxies of investor sentiment.

The findings also show that only fund size has a significant impact on the unadjusted return performance of passive funds. The coefficient of 0.0067 indicates that a one-unit increase in fund size corresponds to a 0.0067% increase in the unadjusted return performance of passive mutual funds. The statistical significance at the 1% level suggests that larger funds tend to have slightly higher returns. This finding aligns with the theory of economies of scale in the fund industry, whereby larger funds may benefit from lower costs and increased diversification, which potentially contributes to enhanced returns, This finding is consistent with prior studies (Bodson et al., 2011; Indro et al., 1999; Perold & Salomon, 1991; Tang et al., 2012) that have also found a positive relationship between fund returns and size. Consequently, this study fails to reject Hypothesis 4.M for passive funds. The factors of oil price volatility, fund flows, management expense ratio, fund age and compliance with Islamic law do not show statistically significant effects on the unadjusted return performance of passive mutual funds. The lack of significance for these variables suggests that, in this study, they may not be primary drivers of passive fund unadjusted returns. Therefore, Hypotheses 4.C, 4.E, 4.G, 4.I and 4.K are hereby rejected.

Overall, the multivariate regression results indicate the distinct effects of factors on active and passive mutual fund unadjusted return performance. For active funds, oil price volatility, management expense ratio and fund age were significant, suggesting that market uncertainties, expense ratios and fund experience affect their returns. In contrast, only fund size showed a significant impact on passive fund returns, indicating that economies of scale and increased diversification play a role. The fund-specific factors, such as fund flows, compliance with Islamic law and fund size, were not statistically significant for both types of funds. These findings highlight the varying drivers of the performance of active and passive funds, providing valuable insights for investors to consider when constructing their investment portfolios.

Table 7.4

Pooled OLS Regressions: Measuring the Impact of Investor Sentiment, Oil Price Volatility and Fund-Specific Factors on Active Fund Unadjusted Return Performance

Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.01359***	0.01499***								
	(0.001)	(0.00098)								
Market turnover			0.13464***	0.14045***						
			(0.00736)	(0.00775)						
Avg. P/E ratio					0.01874***	0.01843***				
					(0.00278)	(0.00282)				
Bull–bear ratio							0.02575***	0.02624***		
							(0.00029)	(0.00029)		
IPCSI-SA									0.06200***	0.04891***
									(0.02282)	(0.02365)
Oil price volatility		-0.37762***		-0.33535***		-0.32873***		-00.36333***		-0.3180***
		(0.06854)		(0.06775)		(0.06713)		(0.03457)		(0.06848)
Fund flows		-0.00008		-0.00008		-0.00009		-0.00015		-0.00009
		(0.00019)		(0.00018)		(0.00018)		(0.00016)		(0.00018)
Management expense ratio		0.15442***		0.14759***		0.14127**		0.10553***		0.13522**
		(0.05613)		(0.05590)		(0.05673)		(0.03361)		(0.05723)
Fund age		0.00334**		0.00328**		0.00078		-0.00448***		0.00146
		(0.00162)		(0.00160)		(0.00162)		(0.00126)		(0.00164)
Compliance with Islamic law		-0.00092		-0.00115		-0.00018		-0.00001		-0.00042
		(0.00182)		(0.00181)		(0.00181)		(0.00151)		(0.00183)
Fund size		-0.00038		-0.00045		0.00037		0.00107***		0.00017
		(0.00043)		(0.00043)		(0.00042)		(0.00034)		(0.00042)
Constant	-0.29371***	-0.32103***	-0.01346***	-0.01017	0.00316***	-0.00329	0.00424***	-0.00308	0.00268***	-0.00117
	(0.02102)	(0.0207)	(0.00123)	(0.00694)	(0.00068)	0.00707	(0.00052)	(0.00533)	(0.00069)	(0.00709)
Obs.	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489
R^2	0.0144	0.0254	0.0208	0.0301	0.0024	0.0109	0.3970	0.4118	0.0016	0.0092
F-statistic	201.93***	45.58***	334.40***	60.59***	45.52***	12.15***	7666.15***	1347.02***	7.38***	6.33***

Note. The table reports the results of pooled OLS regressions of unadjusted returns of active mutual funds on investor sentiment independently in Models 1, 3, 5, 7 and 9. Moreover, in Models 2, 4, 6, 8 and 10, it reports the results of pooled OLS regressions of unadjusted returns of active mutual funds on investor sentiment in addition to oil price volatility and fund-specific factors including fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. Statistical tests for the models such as *F*-statistic and *R*-squared are also reported. To identify the best approach for the estimation, the study performed the Chow (1960) test to compare the pooled OLS model and the fixed-effect model; the Breusch and Pagan (1980) Lagrange multiplier test to compare the pooled OLS model and the random-effect model; and the Hausman (1978) test to compare the fixed-effect model and the random-effect model. These procedures of model selection tests indicated that the pooled OLS regression estimation approach is the most appropriate approach for estimation. The models are estimated with heteroscedasticity robust standard errors (in parentheses). ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7.5

Pooled OLS Regressions: Measuring the Impact of Investor Sentiment, Oil Price Volatility and Fund-Specific Factors on Passive Fund Unadjusted Return Performance

Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.01530***	0.01619***								
	(0.00329)	(0.00328)								
Market turnover			0.12789***	0.12775***						
			(0.02250)	(0.02257)						
Avg. P/E ratio					0.01049	0.01064				
					(0.00974)	(0.00961)				
Bull–bear ratio							0.02682***	0.02707***		
							(0.00088)	(0.00087)		
IPCSI-SA									0.04142	0.01808
									(0.04592)	(0.04517)
Oil price volatility		-0.21281		-0.16442		-0.18502		-0.19439**		-0.17796
		(0.22734)		(0.22378)		(0.22507)		(0.08416)		(0.22597)
Fund flows		-0.00728		-0.00709		-0.00706		-0.0062***		-0.00701
		(0.00493)		(0.00489)		(0.00517)		(0.00172)		(0.00534)
Management expense ratio		0.01644		-0.00058		0.05370		0.07197		-0.00087
		(0.14774)		(0.14756)		(0.14962)		(0.08987)		(0.15085)
Fund age		0.00270		0.00350		0.00395		0.00343		0.00457
		(0.00527)		(0.00523)		(0.00538)		(0.00392)		(0.00542)
Compliance with Islamic law		-0.00091		-0.00054		-0.00143		-0.00108		-0.00114
		(0.00397)		(0.00396)		(0.00402)		(0.00255)		(0.0041)
Fund size		0.00678**		0.00638**		0.00679**		0.00669**		0.00662**
		(0.002989)		(0.00299)		(0.00315)		(0.00267)		(0.00316)
Constant	-0.3315***	-0.4619***	-0.0137***	-0.12032**	0.00303	-0.1112**	0.00241**	-0.11013**	0.00216	-0.10929**
	(0.07179)	(0.09276)	(0.00334)	(0.05445)	(0.00194)	(0.05704)	(0.00123)	(0.04834)	(0.00197)	(0.05723)
Obs.	805	791	805	791	805	791	805	791	805	791
R^2	0.0257	0.0511	0.0337	0.0561	0.0012	0.0240	0.5964	0.6229	0.0009	0.0236
F-statistic	21.57***	4.47***	32.32***	5.56***	1.16	1.29	934.56***	145.53***	0.81	1.14

Note. The table reports the results of pooled OLS regressions of unadjusted returns of passive mutual funds on investor sentiment independently in Models 1, 3, 5, 7 and 9. Moreover, in Models 2, 4, 6, 8 and 10, it reports the results of pooled OLS regressions of unadjusted returns of passive mutual funds on investor sentiment in addition to oil price volatility and fund-specific factors including fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. Statistical tests for the models such as F-statistic and R-squared are also reported. To identify the best approach for the estimation, the study performed the Chow (1960) test to compare the pooled OLS model and the fixed-effect model; the Breusch and Pagan (1980) Lagrange multiplier test to compare the pooled OLS model and the random-effect model; and the Hausman (1978) test to compare the fixed-effect model and the random-effect model. These procedures of model selection tests indicated that the pooled OLS regression estimation approach is the most appropriate approach for estimation. The models are estimated with heteroscedasticity robust standard errors (in parentheses). ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

7.3.3 Measuring the Impact of Investor Sentiment on Risk-Adjusted Returns

Tables 7.6 and 7.7 present the outcomes of pooled OLS regressions for analysing the risk-adjusted return performance of active and passive mutual funds across several factors. These factors encompass investor sentiment, oil price volatility, fund net flow, management expense ratio, fund age, compliance with Islamic law and fund size. The study explores the impact of these factors on the risk-adjusted return performance of active and passive funds, which is estimated against three different benchmark indices: TASI (Panel A), MSCI-SADI (Panel B) and S&P-SADITR (Panel C). However, this section focuses only on the univariate regressions (1, 3, 5, 7, and 9), individually regressing each proxy of investor sentiment, namely trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA, on returns. The results related to active funds are discussed in Subsection 7.3.3.1, while the results related to passive funds are discussed in Subsection 7.3.3.2

7.3.3.1 Impact of Investor Sentiment on Risk-Adjusted Returns of Active Funds

The results in Models 1, 3, 5, 7 and 9 in Table 7.6 are the outcome of univariate pooled OLS regressions of only investor sentiment on active mutual fund risk-adjusted returns. The findings demonstrate that all proxies of investor sentiment have a positive and significant impact on the active mutual fund risk-adjusted return performance, indicating a strong and robust relationship between investor sentiment and the performance of these funds. Starting with Panel A, in Model 1, a one-unit increase in trading volume is associated with a 0.0014 increase in the risk-adjusted returns of active mutual funds. This result implies that a higher trading volume in the overall market positively influences active fund managers' ability to generate risk-adjusted returns. That is, investors' increased activity in the market potentially leads to more opportunities for active fund managers to capitalise on mispriced assets and earn abnormal returns. Model 3 indicates that for every 1% rise in the market turnover ratio, active fund risk-adjusted returns increase by 0.0155%. The higher impact of the market turnover ratio than of the trading volume indicates that the frequency of buying and selling of stocks in the market is a more significant factor affecting the performance of active mutual funds. It suggests that periods of increased trading and higher market activity are conducive to active fund managers' ability to outperform the market. In Model 5, a 1% change in the P/E ratio leads to a 0.0034 increase in the risk-adjusted returns of active funds. This positive impact indicates that shifts in market sentiment, reflected in stock valuations relative to earnings, affect the performance of active funds. When investors are willing to pay a premium for stocks (higher P/E ratio), active fund managers are more likely to generate higher-than-expected returns. Next, the coefficient of Model 7 shows that a 1% increase in the bull–bear ratio results in a 0.0003% increase in the risk-adjusted returns of active funds. This result suggests that changes in the relative sentiment of bullish and bearish investors affect active fund returns to a lesser extent than do other sentiment proxies. However, even small shifts in sentiment can still contribute to fund performance. Last, the IPCSI-SA has the most substantial impact among all the sentiment proxies. A 1% change in IPCSI-SA results in a 0.061% increase in the risk-adjusted returns of active funds. This indicates that IPCSI-SA likely captures investor sentiment more comprehensively, which significantly influences active fund managers' ability to achieve abnormal returns

Further, Panel B and Panel C reveal a striking similarity between the results of the influence of investor sentiment on the risk-adjusted returns of active funds that are adjusted against TASI and those adjusted against MSCI-SADI and S&P-SADITR. Specifically, Panel B shows that a 1% increase in the trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA is associated with a 0.0018, 0.0222, 0.0024, 0.0009 and 0.0529 increase, respectively, in the risk-adjusted returns of active mutual funds. Similarly, the results in Panel C show that a 1% increase in the trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA is associated with a 0.0014, 0.0128, 0.0027, 0.0003 and 0.0623 increase, respectively, in these returns. This remarkable consistency in findings significantly enhances the robustness and reliability of this study's research outcomes. Furthermore, these findings align with those of prior studies that have shown a significant impact of investor sentiment on the returns and volatility of the Saudi Arabian main stock market (Alnafea & Chebbi, 2022; Altuwaijri, 2016). As indicated in Table 7.6, the study does not reject Hypothesis 4.B for active mutual funds. These results shed light on the degree to which investor sentiment influences the unadjusted returns of active and passive funds, providing valuable insights into market dynamics.

The findings of this study yield important implications for academia, investment practices and policymaking. The findings contribute to the academic understanding of the relationship between investor sentiment and mutual fund performance. Specifically, the findings identify the extent to which fund risk-adjusted performance is driven by investor sentiment. The observed positive impact of investor sentiment on mutual fund abnormal returns also raises a question regarding market efficiency. The consistent influence of investor sentiment on the performance of active funds challenges the EMH. These findings suggest that sentiment-driven anomalies persist in the market, creating opportunities for skilled active fund managers to capitalise on market inefficiencies. Investor sentiment exerts a significant influence on financial behaviour, and by studying the impact of investor sentiment on mutual fund performance, researchers can assess how emotions and sentiment-driven behaviour influence active fund performance.

Moreover, the results may assist individual and institutional investors in investment decision-making. Understanding the positive impact of investor sentiment on active mutual fund abnormal returns can influence investors' allocation decisions. If they recognise that sentiment plays a role in driving fund performance, they may adjust their investment strategies accordingly. Furthermore, grasping the influence of investor sentiment on mutual fund returns allows fund managers to consider sentiment indicators alongside other fundamental and technical factors when making investment decisions. Financial institutions and analysts may place increased value on these sentiment proxies, incorporating them into their forecasting models and investment strategies. Last, the findings may have broader policy implications. The market authority and policymakers can utilise these results to enact suitable capital market laws, investor protection measures and market surveillance mechanisms to ensure the stability and integrity of the financial system.

7.3.3.2 Impact of Investor Sentiment on Risk-Adjusted Returns of Passive Funds

In contrast to the results presented in the previous section, the univariate regression results in Models 1, 3, 5, 7 and 9 in Table 7.7 (Panels A, B and C) demonstrate inconsistent significant impact of proxies of investor sentiment on the passive fund risk-adjusted return performance. Specifically, it is evident that only the trading volume has a consistent significant relationship with the risk-adjusted returns of passive funds. However, the other proxies, such as the market turnover ratio, P/E ratio, bull–bear ratio and IPCSI-SA, do not exhibit a consistent statistically significant impact on these returns. From these results, it can be concluded that the overall evidence may not be reliable enough to confirm the existence of a significant investor sentiment impact on passive fund risk-adjusted returns. This lack of a significant impact can be attributed to the passive nature of these funds and their focus on tracking a benchmark. Passive funds aim to replicate market performance rather than outperform the market, making them less sensitive to short-term sentiment-driven fluctuations. Based on the results in Table 7.6, the study rejects Hypothesis 4.B for passive mutual funds.

7.3.4 Measuring the Impact of Investor Sentiment and Fund-Specific Factors on Risk-Adjusted Returns

While the preceding section (7.3.1) focused on univariate regressions that independently assessed the impact of each investor sentiment proxy, this section discusses the results in conjunction with fund-specific factors. In this section, the multivariate regressions (2, 4, 6, 8 and 10) in Table 7.6 and Table 7.7 consider each proxy of investor sentiment along with the other independent variables, investigating their impact on the risk-adjusted return performance of active and passive mutual funds. The multivariate regressions incorporated investor sentiment, oil price volatility and fund-specific factors such as the fund flow, management expense ratio, fund age, compliance with Islamic law and fund size. The results for active funds are discussed in Subsection 7.3.4.1, whereas those for passive funds are discussed in Subsection 7.3.4.2.

7.3.4.1 Impact of Investor Sentiment and Fund-Specific Factors on Risk-Adjusted Returns of Active Funds

The multivariate regressions of Models 2, 4, 6, 8 and 10 in Table 7.6 consider the influence of oil price volatility and fund-specific factors in addition to that of investor sentiment, on active mutual fund risk-adjusted return performance. Overall, Models 2, 4, 6, 8 and 10 consistently exhibit superior explanatory power in capturing variations in the risk-adjusted returns of active funds. The results confirm that these returns exhibit a significant and positive responsiveness to investor sentiment. These findings closely align with the results obtained from the univariate pooled OLS regressions across all proxies of investor sentiment.

The findings suggest that oil price volatility and the fund-specific factors, except fund flow, significantly affect active mutual fund risk-adjusted return performance. First, in line with the findings on the influence on unadjusted returns, it is evident that oil price volatility also exerts a negative impact on risk-adjusted returns. The obtained coefficient of −0.08 indicates that a 1% increase in oil price volatility corresponds to a 0.08% decrease in the risk-adjusted return performance of active mutual funds. The statistical significance at the 1% level further emphasises the significant adverse effect of oil price volatility on fund returns. Higher fluctuations in oil prices can result in market uncertainties and have a negative influence on fund performance. This finding aligns with those of earlier studies that have demonstrated the transmission of volatility between oil prices and the Saudi Arabian equity market (Almohaimeed & Harrathi, 2013; Arouri et al., 2011). Furthermore, these results reinforce the findings of earlier studies on the negative influence of oil market volatility on the risk-adjusted returns of mutual funds (Alsubaiei et al., 2024). As a result, the study fails to reject Hypothesis 4.D for active mutual funds.

Next, the coefficient of 0.10 for the management expense ratio indicates that a 1% increase in this ratio leads to a 0.15% increase in the risk-adjusted return performance of active mutual funds. The results establish a significant relationship at the 1% level, suggesting that higher expense ratios are associated with better risk-adjusted returns for these funds. Whereas most studies, such as those of Ferreira et al. (2013) and Mansor et al. (2015), have reported a negative relationship between the expense ratio and fund performance, the current study's findings aligns with those of other studies, specifically the studies by Díaz-Mendoza et al. (2014) and Droms and Walker (1996), which found a positive relationship between the expense ratio and active fund returns. This positive relationship can be attributed to the fact that funds with higher risk-adjusted returns often charge higher management fees. Consequently, the results contradict Hypothesis 4.H, which proposed a negative impact of the expense ratio on active mutual fund performance and, instead, demonstrate a statistically significant positive impact.

Further, the coefficient 0.0022 for fund age indicates that a one-month increase in the age of active mutual funds corresponds to an approximate slight decrease of 0.0022% in their risk-adjusted return performance. This negative relationship is statistically significant at the 1% level, suggesting that as mutual funds mature and become older, their risk-adjusted returns tend to decline slightly. Therefore, the empirical results reject Hypothesis 4.J of a positive impact and reveal a statistically significant negative impact of fund age on active mutual fund risk-adjusted performance. These findings differ from those of studies on developed markets, including studies conducted by Ferreira et al. (2013), Lou (2012), Pollet and Wilson (2008), Tang et al. (2012) and Yan (2008), which found no significant influence of fund age on mutual fund performance. However, the present study's results align with Ferreira et al.'s (2013) findings regarding non-US funds. The older funds face increased competition from newer funds that might offer more innovative strategies or have access to emerging investment opportunities. This competition can affect the older fund's ability to sustain superior returns.

Moreover, with the enormous growth of Islamic financial instruments, increasing attention is being paid to the impact of compliance with Islamic law on the risk-adjusted performance of active funds. The current empirical evidence reveals that funds compliant with Islamic law exhibit a slightly higher risk-adjusted performance, approximately 0.0011, than conventional funds. These results align with Hypothesis 4.L, which suggests a positive influence of compliance with Islamic law on the risk-adjusted performance of active mutual funds. Moreover, these findings are consistent with those of Ashraf (2013) and Alqadhib et al. (2022), who found that Islamic law has a positive influence on mutual fund performance. The superior performance of Islamic mutual funds can be attributed to their emphasis on riskier assets. By avoiding debt-based investments and focusing on equity for short-term investments, Islamic mutual funds have demonstrated their ability to achieve higher returns. This approach aligns with the principles of Islamic finance and contributes to the observed outperformance.

Last, one of the most debatable factors influencing active mutual funds is their size. There are two competing theories regarding the relationship between fund size and performance. The first theory suggests a negative correlation, attributing it to diseconomies of scale resulting from increased transaction costs as the fund grows (Chan et al., 2009; J. Chen et al., 2004; Yan, 2008). The second theory proposes a positive association, arguing that mutual fund performance improves with an increase in fund size (Bodson et al., 2011; Indro et al., 1999; Perold & Salomon, 1991; Tang et al., 2012). The empirical findings of this study align with the latter theory, revealing a positive and significant coefficient of approximately 0.0011. As a result, the study fails to reject Hypothesis 4.N, which posits a positive relationship between mutual fund performance and fund size. Notably, the study did not discover sufficient evidence to support the impact of fund flow on active fund risk-adjusted return performance. As a result, Hypothesis 4.F is hereby rejected for active funds. Importantly, the findings show a striking similarity as regards the influence of fund-specific factors on fund performance when estimated against TASI, MSCI-SADI and S&P-SADITR. This remarkable consistency significantly enhances the robustness and reliability of the research outcomes.

7.3.4.2 Impact of Investor Sentiment and Fund-Specific Factors on Risk-Adjusted Returns of Passive Funds

The multivariate regression results of Models 2, 4, 6, 8 and 10 in Table 7.7 relate to the potential influence of oil price volatility and fund-specific factors, in addition to investor sentiment, on the risk-adjusted returns of passive funds. The empirical result reveal unexpected and intriguing findings. In alignment with the results derived from the univariate pooled OLS regressions, only Model 2 demonstrates enhanced explanatory power in capturing variations in the risk-adjusted returns of passive funds (across Panels A, B and C). The findings confirm that these returns exhibit a significant and positive responsiveness to trading volume.

In contrast to the findings presented earlier in the current study, which suggested a negative impact of oil price volatility on active funds, this study uncovers that oil price volatility actually has a significant positive effect on passive fund risk-adjusted returns. The coefficient obtained, approximately 0.16, indicates that a 1% increase in oil price volatility corresponds to a 0.16% increase in the risk-adjusted return performance of passive mutual funds. The statistical significance at the 5% and 1% levels further emphasises the substantial positive influence of oil price volatility on passive fund returns. Consequently, the empirical results reject Hypothesis 4.D, which proposes a negative impact, and instead provide strong evidence of a statistically significant positive impact of oil price volatility on passive mutual fund risk-adjusted performance. The differing influence direction of oil price volatility on the risk-adjusted return of active and passive funds may be attributed to the nature of passive investing, lower costs and the composition of market indices.

As discussed in detail in Chapter 3, there are two hypotheses that explain the influence of mutual fund flows on fund performance. The first one is the ‘smart money hypothesis’, proposed by Gruber (1996), which assumes a positive impact of fund flow on its performance, as investors can identify skilled managers and direct their investments accordingly. The second hypothesis is the ‘persistent-flow hypothesis’, which suggests that fund flows persist over time. This means that mutual funds that have experienced outflows in the past are likely to face further redemptions, leading to a decrease in their assets, which in turn deteriorates their performance (see, e.g. G. Jiang & Yuksel, 2017; Lou, 2012; Wermers, 2003). The empirical results of this study support the latter theory, for they reveal a negative and statistically significant coefficient of approximately −0.0047. Consequently, the empirical findings reject Hypothesis 4.F, which posited a positive relationship between mutual fund performance and fund flow. Instead, the results provide compelling evidence of a statistically significant negative impact of flow on passive mutual fund risk-adjusted performance.

Last, as in the case of active funds, this study’s empirical findings demonstrate a positive and significant impact of size on passive fund risk-adjusted performance, supporting the theory of economies of scale. Specifically, for every one-unit increase in fund size, there is a corresponding 0.0072% increase in passive fund risk-adjusted return performance. Consequently, Hypothesis 4.N, which suggests a positive relationship between mutual fund performance and fund size, stands unchallenged and is further reinforced by the evidence provided on passive funds. However, there is insufficient evidence to support the impact of the management expense ratio, fund age and compliance with Islamic law on passive fund risk-adjusted return performance. Consequently, Hypotheses 4.H, 4.J and 4.L are hereby rejected for passive funds. It is essential to note that the results regarding passive funds should be approached with caution, as they are relatively new to the Saudi Arabian market, and the available data cover only 14 passive funds.

Overall, the tested factors influence active funds and passive funds differently. Specifically, the empirical results indicate that investor sentiment exerts a stronger influence on both the unadjusted and risk-adjusted performance of active funds. However, as for the impact of the fund-specific factors on both types of funds, the findings have been mixed. For instance, oil price volatility and fund flow have exhibited contrasting effects on the risk-adjusted performance of active and passive funds.

Table 7.6

Pooled OLS Regressions: Measuring the Impact of Investor Sentiment, Oil Price Volatility and Fund-Specific Factors on Active Fund Risk-Adjusted Return Performance

Panel A: Risk-adjusted return performance estimated against TASI										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00146***	0.00143***								
	(0.00040)	(0.00042)								
Market turnover			0.01552***	0.01427***						
			(0.00336)	(0.00344)						
Avg. P/E ratio					0.00345***	0.00442***				
					(0.00116)	(0.00117)				
Bull–bear ratio							0.00029*	0.00035**		
							(0.00017)	(0.00018)		
IPCSI-SA									0.06120***	0.06049***
									(0.00541)	(0.00551)
Oil price volatility		-0.08153***		-0.07750**		-0.07597***		-0.07783***		-0.06251***
		(0.01806)		(0.01796)		(0.01790)		(0.01776)		(0.01823)
Fund flows		0.00007		0.00007		0.00007		0.00007		0.00007
		(0.00006)		(0.00006)		(0.00006)		(0.00006)		(0.00006)
Management expense ratio		0.10541***		0.10479***		0.10395***		0.10379***		0.10103***
		(0.02289)		(0.02287)		(0.02289)		(0.02289)		(0.02296)
Fund age		-0.00224***		-0.00223***		-0.00253***		-0.00254***		-0.0025***
		(0.00085)		(0.00084)		(0.00083)		(0.00083)		(0.00083)
Compliance with Islamic law		0.00108**		0.00105**		0.00115**		0.00114**		0.00120**
		(0.00054)		(0.00054)		(0.00054)		(0.00054)		(0.00054)
Fund size		0.00106***		0.00105***		0.00114***		0.00113***		0.00112***
		(0.00029)		(0.00028)		(0.00028)		(0.00113)		(0.00028)
Constant	-0.03004***	-0.04703***	-0.00017	-0.01742***	0.00175***	-0.01681***	0.00176***	-0.01666***	0.00164***	-0.01677***
	(0.00861)	(0.00887)	(0.00047)	(0.00420)	(0.00025)	(0.00422)	(0.00025)	(0.00423)	(0.00025)	(0.00424)
Obs.	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489
R^2	0.0012	0.0129	0.0021	0.0134	0.001	0.0127	0.003	0.0123	0.0114	0.0224
F-statistic	13.55***	11.67***	21.28***	12.27***	8.81***	11.05***	3.22*	9.08***	127.98***	24.24***

Table 7.6 (Continued)

Panel B: Risk-adjusted return performance estimated against MSCI-SADI										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00186***	0.00184***								
	(0.00039)	(0.00041)								
Market turnover			0.02222***	0.02106***						
			(0.00333)	(0.00338)						
Avg. P/E ratio					0.00245*	0.0026866**				
					(0.00139)	(0.0011648)				
Bull–bear ratio							0.00096***	0.00107***		
							(0.00018)	(0.00018)		
IPCSI-SA									0.05296***	0.05158***
									(0.00553)	(0.00564)
Oil price volatility		-0.08888***		-0.08370***		-0.08274***		-0.0848***		-0.07157***
		(0.01901)		(0.01888)		(0.01885)		(0.01813)		(0.01918)
Fund flows		0.00007		0.00007		0.00007		0.00007		0.00007
		(0.00006)		(0.00006)		(0.00006)		(0.00006)		(0.00006)
Management expense ratio		0.10426***		0.10355***		0.10261***		0.10130***		0.09998***
		(0.02363)		(0.02360)		(0.02365)		(0.02357)		(0.02378)
Fund age		-0.00206**		-0.00201**		-0.00238***		-0.00257***		-0.00240***
		(0.00086)		(0.00085)		(0.00085)		(0.00085)		(0.00085)
Compliance with Islamic law		0.00101*		0.00096*		0.00110**		0.00110**		0.00117**
		(0.00054)		(0.00054)		(0.00053)		(0.00053)		(0.00054)
Fund size		0.00101***		0.00098***		0.00110***		0.00113***		0.00110***
		(0.00029)		(0.00029)		(0.00028)		(0.00028)		(0.00028)
Constant	-0.03922***	-0.05565***	-0.00139***	-0.01772***	-0.0558744*	-0.01668***	0.00140***	-0.0166***	0.00128***	-0.0168***
	(0.00859)	(0.00884)	(0.00047)	(0.00421)	(0.03046)	(0.00424)	(0.00029)	(0.00423)	(0.00025)	(0.00426)
Obs.	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489
R^2	0.0020	0.0137	0.0042	0.0154	0.0041	0.0121	0.0041	0.0168	0.0084	0.0196
F-statistic	22.16***	12.71***	44.59***	15.47***	3.13*	9.42***	29.47***	12.52***	91.78***	19.07***

Table 7.6 (Continued)

Panel C: Risk-adjusted return performance estimated against S&P-SADITR										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00148***	0.00154***								
	(0.00039)	(0.00041)								
Market turnover			0.01289***	0.01144***						
			(0.00329)	(0.00338)						
Avg. P/E ratio					0.00277**	0.00362***				
					(0.00114)	(0.00116)				
Bull–bear ratio							0.00036**	0.00046**		
							(0.00018)	(0.00018)		
IPCSI-SA									0.06235***	0.06030***
									(0.00543)	(0.00553)
Oil price volatility		-0.11504		-0.11070***		-0.10945***		-0.11115***		-0.09599***
		(0.01829)		(0.01818)		(0.01814)		(0.01790)		(0.01847)
Fund flows		0.00007		0.00007		0.00007		0.00006		0.00006
		(0.00006)		(0.00006)		(0.00006)		(0.00006)		(0.00007)
Management expense ratio		0.09916		0.09836***		0.09768***		0.09732***		0.09480***
		(0.02272)		(0.02272)		(0.02273)		(0.02272)		(0.02281)
Fund age		-0.00257***		-0.00262***		-0.00285***		-0.00290***		-0.00285***
		(0.00085)		(0.00084)		(0.00083)		(0.00083)		(0.00083)
Compliance with Islamic law		0.00091*		0.00091*		0.00099*		0.00098*		0.00105**
		(0.00054)		(0.00054)		(0.00053)		(0.00053)		(0.00053)
Fund size		0.00099***		0.00099***		0.00107***		0.00107***		0.00106***
		(0.00029)		(0.00028)		(0.00028)		(0.00028)		(0.00028)
Constant	-0.03268***	-0.04863***	-0.00192***	-0.01665***	-0.00033*	-0.01617***	-0.00031	-0.01604***	-0.00042*	-0.01621***
	(0.00851)	(0.00878)	(0.00047)	(0.00418)	(0.00025)	(0.00421)	(0.00025)	(0.00421)	(0.00025)	(0.00423)
Obs.	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489	9,775	9,489
R^2	0.0013	0.0159	0.0014	0.0157	0.004	0.0152	0.006	0.0155	0.0119	0.0254
F-statistic	14.35***	13.95***	15.34***	13.20***	5.88**	12.58***	4.15**	11.29***	131.95***	26.27***

Note. The table reports the results of pooled OLS regressions of risk-adjusted returns of active mutual funds on investor sentiment independently in Models 1, 3, 5, 7 and 9. Moreover, in Models 2, 4, 6, 8 and 10, it reports the results of pooled OLS regressions of risk-adjusted returns of active mutual funds on investor sentiment in addition to oil price volatility and fund-specific factors including fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. Statistical tests for the models such as F-statistic and R-squared are also reported. To identify the best approach for the estimation, the study performed the Chow (1960) test to compare the pooled OLS model and the fixed-effect model; the Breusch and Pagan (1980) Lagrange multiplier test to compare the pooled OLS model and the random-effect model; and the Hausman (1978) test to compare the fixed-effect model and the random-effect model. These procedures of model selection tests indicated that the pooled OLS regression estimation approach is the most appropriate approach for estimation. The models are estimated with heteroscedasticity robust standard errors (in parentheses). ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7.7

Pooled OLS Regressions: Measuring the Impact of Investor Sentiment, Oil Price Volatility and Fund-Specific Factors on Passive Fund Risk-Adjusted Return Performance

Panel A: Risk-adjusted return performance estimated against TASI										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00276* (0.00143)	0.00296** (0.00141)								
Market turnover			0.01926** (0.00976)	0.02048** (0.00959)						
Avg. P/E ratio					-0.00382 (0.00505)	-0.00382 (0.00514)				
Bull–bear ratio							0.0001 (0.0006)	0.00012 (0.00059)		
IPCSI-SA									0.0031 (0.02506)	-0.00096 (0.02409)
Oil price volatility		0.15204** (0.0607)		0.16036*** (0.06145)		0.15577** (0.06104)		0.15663** (0.06149)		0.15850** (0.06167)
Fund flows		-0.00475*** (0.00116)		-0.0047*** (0.00116)		-0.0046*** (0.00118)		-0.0047*** (0.00118)		-0.00473*** (0.00125)
Management expense ratio		0.05984 (0.06376)		0.05789 (0.06356)		0.06516 (0.06451)		0.06624 (0.06455)		0.05595 (0.06479)
Fund age		0.00316 (0.00331)		0.00336 (0.00331)		0.00341 (0.00334)		0.00339 (0.00333)		0.00353 (0.00337)
Compliance with Islamic law		-0.00006 (0.00179)		-0.00001 (0.00179)		-0.00013 (0.00179)		-0.00015 (0.0018)		-0.00024 (0.00183)
Fund size		0.00728*** (0.00250)		0.00721*** (0.00250)		0.00728*** (0.00253)		0.00728*** (0.00253)		0.00730*** (0.00255)
Constant	-0.06048* (0.03144)	-0.19331*** (0.06093)	-0.00260 (0.00171)	-0.1306*** (0.04577)	-0.00007 (0.00091)	-0.1292*** (0.04606)	-0.00007 (0.00091)	-0.1292*** (0.04603)	-0.00021 (0.00093)	-0.12968*** (0.04631)
Obs.	805	791	805	791	805	791	805	791	805	791
R^2	0.0038	0.1017	0.0035	0.1013	0.0007	0.0981	0.0000	0.0974	0.0000	0.0985
F-statistic	3.72*	5.41***	3.89**	5.46***	0.57	5.34***	0.03	5.24***	0.02	5.08***

Table 7.7 (Continued)

Panel B: Risk-adjusted return performance was estimated against MSCI-SADI										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00483*** (0.00146)	0.00502*** (0.00143)								
Market turnover			0.03289*** (0.00992)	0.03413*** (0.00969)						
Avg. P/E ratio					-0.0061 (0.00498)	-0.00618 (0.00502)				
Bull–bear ratio							0.00168*** (0.0006)	0.00170*** (0.00059)		
IPCSI-SA									0.00202 (0.02518)	-0.00187 (0.02411)
Oil price volatility		0.16364*** (0.05914)		0.17764*** (0.06018)		0.17004*** (0.0593)		0.17105*** (0.06597)		0.17192*** (0.06012)
Fund flows		-0.00465*** (0.00132)		-0.00461*** (0.00131)		-0.00457*** (0.00135)		-0.00454*** (0.00117)		-0.00464*** (0.00143)
Management expense ratio		0.05733 (0.06209)		0.05427 (0.06205)		0.06643 (0.06303)		0.06935 (0.06297)		0.06344 (0.06331)
Fund age		0.00323 (0.00328)		0.00350 (0.00328)		0.00365 (0.00333)		0.0036 (0.00328)		0.0037 (0.00336)
Compliance with Islamic law		-0.00023 (0.00178)		-0.00015 (0.00179)		-0.00035 (0.0018)		-0.00036 (0.00179)		-0.00051 (0.00183)
Fund size		0.00753*** (0.00249)		0.00743*** (0.00250)		0.00754*** (0.00255)		0.00753*** (0.00253)		0.00759*** (0.00256)
Constant	-0.10585*** (0.0320)	-0.24290*** (0.06071)	-0.00464*** (0.00173)	-0.13665*** (0.04567)	-0.00032 (0.00092)	-0.13425 (0.04627)	-0.00036 (0.00092)	-0.13415*** (0.04598)	-0.00036 (0.00094)	-0.13503*** (0.04653)
Obs.	805	791	805	791	805	791	805	791	805	791
R^2	10.97***	5.60***	10.99***	5.66***	1.50	5.15***	7.91***	6.22***	0.01	4.75***
F-statistic	0.0114	0.1136	0.0099	0.1120	0.0017	0.1032	0.0104	0.1120	0.9361	0.1022

Table 7.7 (Continued)

Panel C: Risk-adjusted return performance estimated against S&P-SADITR										
Variable	Model									
	1	2	3	4	5	6	7	8	9	10
Trading volume	0.00245*	0.00269**								
	(0.00139)	(0.00136)								
Market turnover			0.01201	0.0129						
			(0.00954)	(0.00930)						
Avg. P/E ratio					-0.00462	-0.00463				
					(0.00493)	(0.00499)				
Bull–bear ratio							0.00022	0.00024		
							(0.00057)	(0.00057)		
IPCSI-SA									0.00396	-0.00141
									(0.02443)	(0.02339)
Oil price volatility		0.12003**		0.12658**		0.12317**		0.12419**		0.12559**
		(0.05886)		(0.05955)		(0.05909)		(0.06010)		(0.05981)
Fund flows		-0.00481***		-0.00477***		-0.00475***		-0.00476***		-0.00479***
		(0.00110)		(0.00111)		(0.00111)		(0.00110)		(0.00118)
Management expense ratio		0.06001		0.06055		0.06455		0.06594		0.05948
		(0.06164)		(0.06145)		(0.0624)		(0.06246)		(0.06270)
Fund age		0.00277		0.00293		0.00299		0.00298		0.00307
		(0.00328)		(0.00329)		(0.00331)		(0.00330)		(0.00334)
Compliance with Islamic law		-0.00025		-0.00024		-0.00030		-0.00032		-0.00046
		(0.00174)		(0.00174)		(0.00173)		(0.00174)		(0.00178)
Fund size		0.00726***		0.00722***		0.00726***		0.00726***		0.00729***
		(0.00248)		(0.00249)		(0.00251)		(0.00251)		(0.00253)
Constant	-0.05587*	-0.18816***	-0.00399**	-0.13068***	-0.00241	-0.12979***	-0.00241	-0.12975***	-0.00250	-0.13048***
	(0.03046)	(0.06014)	(0.00168)	(0.04557)	(0.00088)	(0.04568)	(0.00089)	(0.04564)	(0.00090)	(0.04594)
Obs.	805	791	805	791	805	791	805	791	805	791
R^2	0.0031	0.1020	0.0014	0.0999	0.0011	0.0993	0.0002	0.0985	0.0000	0.0991
F-statistic	3.11*	5.46***	1.59	5.37***	0.88	5.45***	0.14	5.38***	0.03	5.10***

Note. The table reports the results of pooled OLS regressions of risk-adjusted returns of passive mutual funds on investor sentiment independently in Models 1, 3, 5, 7 and 9. Moreover, in Models 2, 4, 6, 8 and 10, it reports the results of pooled OLS regressions of risk-adjusted returns of passive mutual funds on investor sentiment in addition to oil price volatility and fund-specific factors including fund flows, management expense ratio, fund age, compliance with Islamic law and fund size. Statistical tests for the models such as *F*-statistic and *R*-squared are also reported. To identify the best approach for the estimation, the study performed the Chow (1960) test to compare the pooled OLS model and the fixed-effect model; the Breusch and Pagan (1980) Lagrange multiplier test to compare the pooled OLS model and the random-effect model; and the Hausman (1978) test to compare the fixed-effect model and the random-effect model. These procedures of model selection tests indicated that the pooled OLS regression estimation approach is the most appropriate approach for estimation. The models are estimated with heteroscedasticity robust standard errors (in parentheses). ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

7.4 Chapter Summary

This chapter presented the findings on the impact of investor sentiment as a new factor, coupled with fund-specific factors, on the performance of active and passive mutual funds in the Saudi Arabian market. It investigated the extent to which the return performance of these funds is affected by investor sentiments and fund-specific factors. The literature has provided evidence of the positive influence of investor sentiment on the returns and volatility of the Saudi Arabian main stock market (Alnafea & Chebbi, 2022; Altuwaijri, 2016). However, the present study is the first to explore the impact of investor sentiment on the performance of active and passive mutual funds in the Saudi Arabian market. The impact of investor sentiment on mutual fund performance holds significant value, particularly in the Saudi Arabian market, which is intensively dominated by individual investors. First, this chapter demonstrated the relationship between investor sentiment and mutual fund performance, revealing how fund performance is driven by investor sentiment. Second, it would enable wise investors to time their investment decisions in mutual funds according to investor sentiment. Last, researching the impact of investor sentiment on mutual fund performance can have broader policy implications.

The study explored the influence of investor sentiment and fund-specific factors on mutual fund performance. To investigate the potential impact of these factors, this study employed five proxies for investor sentiment: trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA. Simultaneously, the analysis considered fund-specific factors, such as funds' net flow, management expense ratio, fund age, compliance with Islamic law and fund size. Two measures of mutual fund return performance served as the dependent variables, namely unadjusted return performance and risk-adjusted return performance. To explore the potential effect of these variables, the study employed panel data analysis. According to Baltagi (2008), this approach mitigates potential estimation bias arising from heteroscedasticity and multicollinearity. The procedures for the model selection tests, outlined in Chapter 4, to determine the suitable model specification for panel data analysis consistently identified the pooled OLS regression model.

The first part of the analysis involved examining the impact of each proxy of investor sentiment on the unadjusted returns of active and passive mutual funds independently and in conjunction with fund-specific factors. The analysis results showed that all proxies of investor sentiment had a positive impact on the unadjusted returns of active funds. The trading volume, market turnover ratio, average P/E ratio, bull–bear ratio and IPCSI-SA exhibited statistically significant positive relationships with active fund returns. These findings suggest that increased market activity, positive shifts in sentiment and optimistic investor behaviour contribute to higher unadjusted returns for active mutual funds. In contrast, the impact of investor sentiment on passive fund returns was less pronounced, with only trading volume showing a consistent significant relationship. This discrepancy can be attributed to the passive nature of these funds, which aim to replicate market performance rather than capitalise on sentiment-driven opportunities.

Generally, incorporating oil price volatility, and fund-specific factors in conjunction with investor sentiment, consistently demonstrated higher explanatory power in capturing the variations in unadjusted returns of both active and passive funds. The results confirmed that the unadjusted returns of active funds are significantly and positively responsive to investor sentiment. Moreover, oil price volatility, management expense ratio, fund age, compliance with Islamic law and fund size significantly influenced the unadjusted returns of active funds. Higher oil price volatility had a negative effect on active fund returns, while higher management expense ratios and fund age were associated with increased unadjusted returns. Compliance with Islamic law and larger fund size also showed positive relationships with active fund returns, indicating economies of scale.

Similarly, the results showed a significant and positive correlation between passive fund unadjusted returns and three key proxies of investor sentiment: trading volume, market turnover and bull–bear ratio. However, fund flow, compliance with Islamic law and fund size did not exhibit significant effects on the unadjusted returns of passive funds.

The second part of this analysis involved investigating the impact of each proxy of investor sentiment on the risk-adjusted returns of active and passive mutual funds independently and in conjunction with fund-specific factors. The analysis results revealed that all proxies of investor sentiment had positive and significant effects on the risk-adjusted returns of active funds, indicating a robust relationship between investor sentiment and their performance. This suggests that sentiment-driven anomalies persist in the market, potentially creating opportunities for skilled active fund managers to capitalise on market inefficiencies. However, the impact of investor sentiment on passive fund risk-adjusted returns was less consistent, with only trading volume showing a significant relationship. This finding further emphasises the difference in the influence of investor sentiment based on the investment strategies of active and passive funds.

The inclusion of oil price volatility and fund-specific factors, along with investor sentiment, has provided better explanations of the variations in risk-adjusted returns of active funds. The results confirm that returns from active mutual funds exhibit a significant and positive responsiveness to investor sentiment. Importantly, there is a remarkable alignment in the impact of the various factors on fund risk-adjusted return performance when assessed against TASI, MSCI-SADI and S&P-SADITR. This consistency underscores the robustness and reliability of these results. The findings show that oil price volatility, management expense ratio, fund age, compliance with Islamic law and fund size significantly affected the risk-adjusted returns of active funds. Higher oil price volatility had a negative effect on active fund risk-adjusted returns, while higher management expense ratios and fund age were associated with increased risk-adjusted returns. Compliance with Islamic law and larger fund size also showed positive relationships with active fund risk-adjusted returns, reinforcing the importance of these factors in driving fund performance. Overall, these findings align with the results of past studies in this area (Alsubaiei et al., 2024; Ashraf, 2013). However, fund flow did not exhibit a significant impact on active fund risk-adjusted returns. Surprisingly, for passive funds, the study observed a positive impact of oil price volatility on their risk-adjusted returns, contrary to the negative effect found for active funds. This positive impact on passive funds in Saudi Arabia could be attributed to the nature of passive investing, lower costs and the composition of market indices. Last, fund flow significantly and negatively influenced the risk-adjusted returns of passive funds.

Overall, this empirical analysis has provided valuable insights into the drivers of mutual fund performance in the Saudi Arabian market. The positive impact of investor sentiment on both the unadjusted and risk-adjusted returns of active funds challenges the EMH and highlights the role of sentiment-driven anomalies in driving fund performance. This finding has significant implications for investors, fund managers and policymakers, who can use this information to make informed investment decisions and develop appropriate capital market regulations. This study suggests stronger market surveillance to monitor unusual trading patterns that may be driven by sentiment rather than fundamental factors. Moreover, this study recommends enhancing the transparency requirements for mutual funds to ensure that investors can make more informed decisions, rather than investing in mutual funds based on the prediction of investor sentiment.

Chapter 8: Impact of COVID-19 on Mutual Fund Performance in Saudi Arabia[43] [44]

8.1 Introduction and Background

The recent global outbreak of COVID-19 has caused high economic uncertainty in financial markets. The unprecedented wide-ranging economic repercussions of this pandemic have disrupted normal operations in all economic sectors. Globally, most cities imposed stay-at-home orders to contain the spread of the virus, causing severe losses to most business sectors. Brent oil prices plunged more than 65% during the first quarter of 2020, and the US crude oil futures collapsed below zero for the first time in history (Sheppard et al., 2020). The World Bank Group (2020) reported a decline of 5.2% in the overall global GDP. Among others, the global equity market has been considered to be one of the most affected sectors in the global economy.

This scenario motivated numerous researchers to uncover the impact of COVID-19 on stock pricing behaviour around the globe (Al-Awadhi et al., 2020; Erdem, 2020; Mazur et al., 2021; M. L. Rahman et al., 2021; Xu, 2021). Although they used different approaches to identify this impact, most of these studies arrived at a consensus that stock returns have been negatively affected by this pandemic. Moreover, Engelhardt et al. (2021) and X. Gao et al. (2021) provided evidence of the impact of COVID-19 on stock market volatility, and Zaremba et al. (2021) showed that responses to COVID-19 affected market liquidity in emerging markets.

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[43] Alqadhib, H., Kulendran, N., & Seelanatha, L. (2022). Impact of COVID-19 on mutual fund performance in Saudi Arabia. *Cogent Economics & Finance*, *10*(1), Article 2056361. https://doi.org/10.1080/23322039.2022.2056361.

[44] To assess the impact of the COVID-19 pandemic on mutual fund performance, this study utilises weekly returns, avoiding noise in daily data and eschewing aggregation at the monthly level. Consequently, this chapter was isolated from the preceding one, aiming to facilitate an understanding of the pandemic's influence on mutual fund performance. This separation enables a more precise evaluation, avoiding overlap with factors studied over a broader time span and exempting it from the lower frequency of monthly data.

This chapter aims to identify the potential impact of both the increase in new confirmed cases of COVID-19 and fatalities on unadjusted returns and risk-adjusted returns across equity mutual funds. The literature has paid less attention to measuring the impact of factors related to the COVID-19 crisis on mutual fund performance in the Middle East's largest market, necessitating further investigation. Thus, testing how fund performance has been affected by the COVID-19 crisis helps in understanding the behaviour of mutual fund performance and the importance of equity mutual funds as an alternative for building a personal investment portfolio during pandemics. It also aims to examine the ability of individual mutual fund managers to alleviate the consequences of the COVID-19 outbreak on the fund performance in comparison to the market portfolio. This exploration would help investors to understand the behaviour of mutual fund managers who protect their wealth from the consequences of the COVID-19 pandemic, compared with the market portfolio.

In Saudi Arabia, the spread of COVID-19 posed serious obstacles in terms of economic indicators. Initially, the Government of Saudi Arabia imposed movement restrictions, such as the suspension of airlines and the elimination of tourism programs and cultural and religious events. Then, they shifted to complete lockdowns and curfew during periods of high growth in new confirmed cases. The real GDP dropped by 4.1% (General Authority for Statistics, 2020), exceeding the World Bank Group (2020) previous forecast of −3.8%. Accordingly, the TASI plunged by approximately 30% between January and April 2020.

The increase in COVID-19 cases affected most stock returns in the Saudi market. Similarly to the governments of all other countries, the Government of Saudi Arabia introduced measures to counter its spread, such as tightening or easing human movement and imposing lockdowns, depending on new confirmed cases. These measures negatively affected the operational performance of the stock market. By confirming the negative impact of COVID-19, Alzyadat and Asfoura (2021) recorded that TSAI returns were negatively associated with the increase of new confirmed cases. The ongoing research in this area is considering the impact of changes in the number of cases as well as the number of fatalities due to COVID-19. Atassi and Yusuf (2021) applied panel data regression models to investigate how both indicators affect market performance. They found that the overall market responded significantly and negatively to an increase in new confirmed cases, and non-significantly and positively to the growth in fatalities. Moreover, Sayed and Eledum (2021) used event study methodology to investigate the short-term response in the Saudi equity market. They showed that within the 9-day event window, the Saudi equity market responded negatively and significantly to confirmed cases. They added that banks, consumer services, capital goods, transportation and commercial services were the most negatively affected industries, whereas telecommunication services and food and beverage were positively affected. Overall, these findings indicate a possibility of mutual fund managers' diversification opportunities being limited during the COVID-19 crisis. However, to the best of this researcher's knowledge, no previous study has attempted to investigate the effect of the COVID-19 outbreak on mutual fund performance.

Managers of equity investment funds employ their expertise to change the compositions of their investments to reflect the changing economic and market conditions in order to manage portfolio risks. By changing the compositions of the funds, they aim to provide the best diversification and achieve superior performance for their investors (Bodie et al., 2010). Thus, fund managers have implemented a similar approach to minimise the adverse impact of COVID-19 on the funds' performance. Therefore, the growth in new cases of COVID-19 may not affect the performance of equity mutual funds significantly. However, the existing evidence on the impact of the increase in COVID-19 cases on the overall Saudi market, provided by Alzyadat and Asfoura (2021), Atassi and Yusuf (2021) and Sayed and Eledum (2021), may reflect the potential impact of the spread of COVID-19 in Saudi Arabia on mutual fund performance, which has not yet been unearthed. Therefore, this study examines the potential impact of the increase in new confirmed cases of COVID-19 and in fatalities, on including other control variables—compliance with Islamic law, management fee, age of funds and size of funds—on the Saudi mutual fund performance.

Hypothesis 5 (5.A): Increases in COVID-19 new cases and in COVID-19 fatalities negatively affect active mutual fund unadjusted return performance.

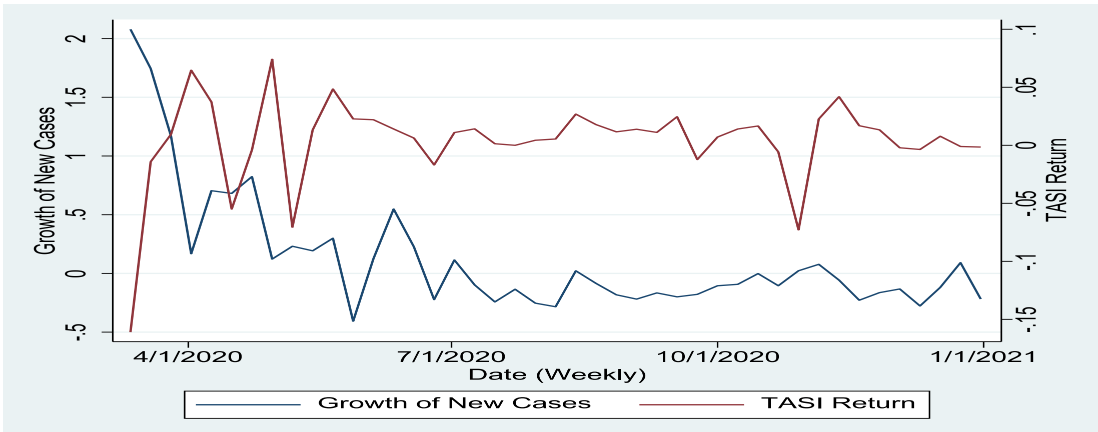
Hypothesis 5 (5.B): Increases in COVID-19 new cases and in COVID-19 fatalities negatively affect active mutual fund risk-adjusted return performance.

Hypothesis 5 (5.C): COVID-19 affected the active mutual funds less severely than it affected the overall market.

Figure 8.1 shows the returns of the main index of the Saudi market (TASI) and the growth of new confirmed cases of COVID-19. It displays the adverse sensitivity of TASI to the growth in these new cases especially during the earlier stages of the virus spread in the country. This study's inferences in Figure 8.1 are consistent with the empirical findings of Alzyadat and Asfoura (2021) and Atassi and Yusuf (2021), who documented an adverse market reaction to the COVID-19 pandemic.

Figure 8.1

Response of TASI Returns to Changes in New Confirmed Cases of COVID-19 (March 2020 – December 2020)



Note. The researchers estimated and analysed the variants in this figure using the Stata software.

8.2 Data and Methodology

COVID-19 data for Saudi Arabia (number of confirmed new cases and fatalities) were obtained from the Ministry of Health's COVID-19 daily report and the daily case numbers were converted to weekly cases. Data for fund net asset values (fund trading prices) and financial ratios were collected from the Refinitiv Datastream database. This chapter focuses on the existing 79 locally invested equity funds. This study relies on weekly returns to avoid the noise in the daily data. It employs 43 time-series return observations for each fund from 5 March to 31 December 2020.

This study predicts that the economic repercussions of the COVID-19 outbreak have negatively affected mutual fund performance. Its effect is measured by considering the change in weekly new infections (CWI) and the change in weekly fatalities (CWF). To test the hypothesised impact of the COVID-19 outbreak on mutual fund performance, this study applies the model in Equation (26).

Panel data regression analysis is the most appropriate approach for this study. As the COVID-19 outbreak occurred over a relatively long period, the use of this approach allows this study to identify the impact of the outbreak over time and across funds. Furthermore, panel data regression models control for both time-series and cross-sectional variation in the data. Thus, it minimises estimation bias issues that could arise from heteroscedasticity and multicollinearity (Baltagi, 2008). Thus, the pooled OLS regression estimation approach is the most appropriate approach to investigate the impact of COVID-19 on mutual fund performance. However, to test the robustness of the results, this study also estimated Equation (26) using a two-way fixed-effect model controlling for both the fund-and-time fixed-effect dummy variables along with the main independent variables, *CWI* and *CWF*. The study estimated the models with heteroscedasticity robust standard errors. Equation (26) is as follows:

$$R_{i,t} = \alpha_i + \beta_1 Cov19_t + \sum_{k=1}^{k} \beta_k \mathrm{X}_{i,k} + \upsilon_{i,t} \tag{26}$$

where $R_{i,t}$ is mutual fund returns (unadjusted return calculated or risk-adjusted return estimated) for the i^{th} fund at week *t*. The unadjusted return performance and the risk-adjusted return performance are determined using Equations (1) and (7)[45] presented in Chapter 4, respectively. α_i is the intercept. The main explanatory variables, *CWI* and *CWF*, are calculated separately using Equation (27), which gives the growth rate and shows how the COVID-19 cases fluctuated in the country. $\mathrm{X}_{i,t}$ is a vector of explanatory variables that are used to control the fund-specific variables.

[45] The study applied FF5FM to estimate risk-adjusted returns instead of FFC6FM because the Carhart momentum factor was not accessible on a weekly frequency.

It includes the management fee, fund size, fund age and a dummy variable to represent compliance with Islamic law. The management fee is the annual fee paid by a fund's subscribers to its managers as a percentage of their investments. The natural logarithm of total net assets (TNA) held by a fund is taken as proxy for the fund size. Age is the number of years elapsed from the inception of a fund. Compliance with Islamic law is a dummy variable that takes the value of 1 for funds defined as compliant with Islamic law by Tadawul, and 0 otherwise.

Equation (27) is a modified version of Equation (1) that has been used to measure the changes in COVID-19 cases (new infections and fatalities). This modified equation is separately estimated for the change in weekly infections (*CWI*) and the weekly change in fatalities (*CWF*) and is as follows:

$$Change\ in\ COVID\ Cases_t = ln\left(\frac{COVID\!-\!19\ Cases_t}{COVID\!-\!19\ Cases_{i(t-1)}}\right) \qquad (27)$$

8.3 Summary Statistics

Tables 8.1 and 8.2 present the summary statistics and the pairwise correlations of the test variables, respectively. During the COVID-19 period from 5 March to 31 December 2020, equity mutual funds gained an average unadjusted return of 0.41% compared with 0.35% for the overall market (TASI) and experienced a slightly lower standard deviation of 3.07% compared with the market's 3.76%. Thus, on average, mutual fund managers in Saudi Arabia provided their investors with higher returns, associated with lower risk, than the market did during the COVID-19 crisis. The average *CWI* and *CWF* were 12.26% and 10.06%, respectively. The pairwise-correlation coefficients for variables show that there is no significant multicollinearity between the dependent variables.

Table 8.1

Summary Statistics of Main Variables Included in Study (March 2020 – December 2020)

Variable	*M*	*SD*	Min	Max
Fund unadjusted return	0.00414	0.03079	-0.24583	0.13303
Fund risk-adjusted return	0.00150	0.01299	-0.09026	0.08896
Islamic-law compliance	0.70886	0.45435	0.00000	1.0000
Management fee	0.03897	0.01019	0.02130	0.06850
Age	11.8860	7.44027	1.0000	29.000
Size	17.5118	1.94670	8.94197	21.55116
CWI	0.12262	0.51165	-0.40668	2.07944
CWF	0.10066	0.36798	-0.31187	1.79175
TASI unadjusted returns	0.00352	0.03767	-0.16099	0.74098

Note. Fund returns are identified as unadjusted returns measured by Equation (1) and risk-adjusted returns are the funds' excess returns over TASI estimated by Equation (7). CWI is the weekly change in COVID-19 new confirmed cases and CWF is the weekly change in the number of COVID-19 fatalities. Islamic law is a dummy variable that signals 1 for funds that follow Islamic laws in their investments. The management fee is the percentage of the annual fees paid by subscribers to the managers of funds. The fund's age is the number of years it has been in operation. Size is the natural logarithm of the TNA of the fund.

Table 8.2

Pairwise Correlations Between Mutual Fund Returns and Other Variables (March 2020 – December 2020)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Fund unadjusted-returns	1.00								
2. Fund risk-adjusted returns	0.4208	1.00							
3. CWI	-0.5185	-0.2465	1.00						
4. CWF	0.1880	0.0253	0.4833	1.00					
5. TASI returns	0.8626	-0.0002	-0.4643	0.2091	1.00				
6. Islamic-law compliance	0.0157	0.0225	0.0000	0.000	0.000	1.00			
7. Management fee	-0.0069	-0.0069	0.0000	0.000	0.000	0.0161	1.00		
8. Age	0.0023	-0.0063	0.0000	0.000	0.000	-0.1745	0.0167	1.00	
9. Size	0.0116	-0.0015	-0.0257	-0.0227	0.0063	0.0158	-0.0303	0.5635	1.00

Note. Fund returns are identified as unadjusted returns measured by Equation (1) and risk-adjusted returns are the funds' excess returns over TASI estimated by Equation (7). CWI is the weekly change in COVID-19 new confirmed cases and CWF is the weekly change in the number of COVID-19 fatalities. Islamic law is a dummy variable that signals 1 for funds that follow Islamic laws in their investments. The management fee is the percentage of the annual fees paid by subscribers to the managers of funds. The fund's age is the number of years it has been in operation. Size is the natural logarithm of the TNA of the fund.

Table 8.3 summarises the estimated FF5FM given in Equation (7). The estimated R-squared shows that the model explains approximately 75% of the equity mutual fund returns. The estimated coefficient for the market risk premium (TASI-RP) shows a significant positive relationship with the mutual fund return. The estimated market systematic risk reveals that a 1% increase in market excess return leads to a 0.68% increase in mutual fund return, indicating that fund returns are less volatile than the overall market returns. The results also show a significant positive association between the size and the value factors and significant negative association of the profitability factor with fund returns. Furthermore, Table 8.3 also records a statistically significant alpha coefficient of 0.15% on mutual fund returns in Saudi Arabia during the study period. The fact that mutual funds gained a significant and positive risk-adjusted return of 0.15% contributes to the theory of superior mutual fund performance during financial crises in developed markets (Kosowski, 2011; Moskowitz, 2000). It also supports the findings about the better performance of Saudi Arabian mutual funds during a financial crisis (Merdad et al., 2010). More importantly, the current findings provide evidence that mutual funds can generate significant positive risk-adjusted returns even after controlling for two additional risk factors of profitability and investment that have never been considered in prior studies. Given that the results of the current study show that the profitability risk factor is statistically significant, this factor may play a dominant role in Saudi mutual funds' expected returns, which necessitates considering it in future research towards ensuring precise performance measurement. However, the current results contradict those of Mirza et al. (2020) and Pástor and Vorsatz (2020), who reported that mutual funds significantly underperformed their benchmarks in developed markets during the COVID-19 pandemic. The contradiction with these studies may be attributed to the classification of market development; as Huij and Post (2011) demonstrated, mutual funds operating in emerging markets perform better than those operating in developed markets.

Table 8.3

Time-Series Regression of Funds' Excess Returns on the FF5FM (March 2020 – December 2020)

Fund's excess returns	Coef.	*SE*	*t*-stat	*p*-value	95% CI	
TASIRP	0.68162	0.02006	33.97	0.000	0.64167	0.72156
SMB	0.04437	0.01522	2.91	0.005	0.01405	0.07468
HML	0.07274	0.01201	6.06	0.000	0.04882	0.09666
RMW	-0.0905	0.01412	-6.41	0.000	-0.11865	-0.06240
CMA	-0.1615	0.01444	-1.12	0.267	-0.04491	0.01261
Cons	0.00150	0.00018	8.03	0.000	0.00113	0.00188
R sqr = 0.7511		F = 295.46		Root MSE = 0.0153		

Note. TASIRP is the market risk premium measured as the return of TASI minus the 1-month SAMA-bills rate of returns. SMB is the difference in returns of small stock portfolios and the big stock portfolios; HML is the difference in returns of the portfolios of high book-to-market ratio and low book-to-market ratio; RMW is the difference in returns of the portfolios of robust operating-income ratio and weak operating-income ratio; CMA is the difference in returns of the portfolios of conservative asset-growth ratio and aggressive asset-growth ratio.

8.4 Empirical Analysis

Table 8.4 presents the estimated pooled OLS regression model given in Equation (26), which investigates the impact of *CWI*, *CWF* and control variables on mutual fund unadjusted returns. The selection of independent variables for estimation includes the following: (1) only *CWI* in the model; (2) both *CWI* and other fund-specific variables in the model; (3) only *CWF* in the model; and (4) both *CWF* and other fund-specific variables in the model. As shown in Table 8.4, *CWI* had a significant negative effect of −3.12% on the mutual fund unadjusted returns in Models (1) and (2). The association between *CWI* and unadjusted returns does not change the estimations with *CWI* in Model (2) even after including the control variables. These results confirm the significant and negative effect of the COVID-19 outbreak on the mutual fund unadjusted returns.

This result fails to reject Hypothesis 5.A that changes in COVID-19 new cases negatively affect active funds' unadjusted return performance. An extended analysis of the impact of the COVID-19 outbreak on individual mutual funds' unadjusted returns is presented later in this chapter. Next, the significant positive effect of compliance with Islamic law on mutual fund performance during the COVID-19 crisis is consistent with Merdad et al.'s (2010) finding that mutual funds compliant with Islamic law performed better during the financial crisis owing to the higher compensations they received for their riskier holdings. Furthermore, this study finds that the age of funds had a significant positive effect on the mutual fund performance during the COVID-19 crisis, indicating the better performance of long-time experienced managers during the financial crisis.

In contrast to the findings of the regression that used *CWI* as an explanatory variable, the regression used to identify the association of *CWF* with unadjusted returns revealed a positive association of 0.0115. This outcome rejects Hypothesis 5.A that changes in new fatalities from COVID-19 negatively affect active funds' unadjusted return performance, confirming a significant positive effect. As explained by Bodie et al. (2010), forward-looking investors use current information to predict market conditions. Therefore, it can be assumed that investors in the market have predicted the *CWF* based on the *CWI* according to the available global average mortality rate of 2.36% (Worldometers, 2021). Investors immediately react to *CWI*, expecting a similar mortality rate in the future. However, the actual mortality rate in Saudi Arabia which started developing 3 weeks following the infection was 1.60% (Worldometers, 2021), which was remarkably lower than what was initially assumed. Therefore, the positive coefficients recorded for the *CWF* may be evidence that the market is adjusting its overestimation of fatalities in advance and reacting to it as positive news.

Table 8.4

Pooled OLS Regression of Funds' Unadjusted Returns on CWI and CWF (March 2020 – December 2020)

Funds' unadjusted return performance	(1)	(2)	(3)	(4)
CWI	-0.0312***	-0.0312***		
	(0.001)	(0.001)		
CWF			0.0115***	0.0115***
			(0.00063)	(0.00063)
Islamic-law compliance		0.00120***		0.00085
		(0.00039)		(0.00062)
Management fee		-0.02284		-0.02416
		(0.02596)		(0.03249)
Age		0.00004*		0.00006
		(0.00002)		(0.00003)
Size		-0.00012		0.00008
		(0.00010)		(0.00015)
Constant	0.00796***	0.00970***	0.00706***	0.00578*
	(0.000)	(0.00258)	(0.00027)	(0.00346)
Obs	3,397	3,397	3,239	3,239
R-sqr	0.2689	0.2692	0.0353	0.0358
F-statistic	943.81	240.72	321.04	80.01

Note. Fund unadjusted return is the dependent variable. Independent variables are CWI, CWF, Islamic law, management fee, age, and size. Islamic law is a dummy variable signals 1 for funds that follow Islamic laws in their investments. Management fee is the percentage of the annual fees paid by subscribers to the managers of funds. The fund's age is the number of years it has been in operation. Size is the natural logarithm of TNA. The model is estimated with heteroscedasticity robust standard errors (in parentheses). ***,**,* Represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8.5 shows the pooled OLS regression estimation of Equation (26) that quantifies the impact of *CWI*, *CWF* and control variables on mutual fund risk-adjusted returns. The following independent variables were chosen for the estimation procedure: (1) only *CWI* model, (2) both *CWI* and other control variables model, (3) only *CWF* model and (4) both *CWF* and other control variables model. As in the case of unadjusted returns, the *CWI* was significant and had a negative impact on the mutual fund risk-adjusted returns. On average, for every 1% increase in new cases, fund risk-adjusted performance declined by approximately 0.0063%. The results remain consistent even after adding fund-specific control variables. Consequently, this result fails to reject Hypothesis 5.B that changes in COVID-19 new cases negatively affected active funds' risk-adjusted return performance. This study did not find sufficient evidence on the impact of other control variables on the mutual fund risk-adjusted returns during the study period except for mutual funds compliant with Islamic law, which are generally compensated for holding riskier equities (Merdad et al., 2010). *CWF* affected risk-adjusted performance positively at the 10% significance level, shown in Models (3) and (4). These results reject Hypothesis 5.B that changes in COVID-19 new fatalities negatively affected active funds' risk-adjusted return performance, confirming a significant positive effect.

Thus, the results of this study provide unprecedented evidence confirming the impact of the spread of COVID-19 cases as a new factor that negatively affected equity mutual funds' unadjusted and risk-adjusted returns in Saudi Arabia. The current findings are consistent with those of Alzyadat and Asfoura (2021) and Atassi and Yusuf (2021), who measured the impact of the COVID-19 outbreak on the Saudi main market index and sub-indices. The negative impact of the COVID-19 outbreak across mutual funds provides evidence of low resilience in their unadjusted and risk-adjusted returns to the economic restrictions associated with the spread of COVID-19. This significant and negative association could have resulted from the counter-asset choices made by the fund managers to overcome the negative effects of COVID-19. The general characteristics of holdings can be inferred from the coefficient signs in Table 8.3. The significant positive *SMB* indicates mutual funds' net sensitivity to small-cap stocks (Omri et al., 2019), which were indeed affected significantly and negatively during the COVID-19 crisis. The net exposure of Saudi mutual funds to these stocks during the crisis could be a reason for the negative impact of the increase in COVID-19 cases on the risk-adjusted returns across mutual funds. However, no information is publicly available on managers' specific equity selection behaviour to verify this claim.

Table 8.5

Pooled OLS Regression of Funds' Risk-Adjusted Returns on CWI and CWF (March 2020 – December 2020)

Fund's risk-adjusted return performance	(1)	(2)	(3)	(4)
CWI	-0.00626***	-0.00626***		
	(0.00061)	(0.00061)		
CWF			0.00079*	0.00079*
			(0.00042)	(0.00042)
Islamic-law compliance		0.00067*		0.00026
		(0.00037)		(0.00047)
Management fee		-0.00976		-0.01189
		(0.01855)		(0.02153)
Age		0.00001		-0.00002
		(0.00003)		(0.00003)
Size		-0.00007		-0.00000
		(0.0001)		(0.00013)
Constant	0.0022***	0.0033*	0.0022***	0.00285
	(0.00020)	(0.00190)	(0.00020)	(0.00246)
Obs	3,397	3,397	3,239	3,239
R-sqr	0.0608	0.0614	0.0006	0.0012
F-statistic	104.49	24.53	3.65	1.12

Note. Funds risk-adjusted return is the dependent variable. Independent variables are CWI, CWF, Islamic law, management fee, age, and size. Islamic law is a dummy variable signals 1 for funds that follow Islamic laws in their investments. Management fee is the percentage of the annual fees paid by subscribers to the managers of funds. The fund's age is the number of years it has been in operation. Size is the natural logarithm of TNA. The model is estimated with heteroscedasticity robust standard errors (in parentheses). ***,**,* Represent statistical significance at 1%, 5%, and 10% levels, respectively.

To conduct a robustness test for the estimations of Equation (26), the fund-level control variables were replaced with dummy variables for fund-fixed effects and time-fixed effects. Table 8.6 shows the estimated results of the model, which confirm that *CWI* continued to have a significant negative impact on both unadjusted and risk-adjusted performance of mutual funds. Moreover, the impact of *CWF* continued to be significant and positive. The results in Table 8.6

confirm that the estimations in Table 8.4 and Table 8.5 are not biased owing to the omitted variables.

Table 8.6

Entity-and-Time Fixed Effect Regression Model of Funds' Unadjusted Returns and Risk-Adjusted Returns on CWI and CWF (March 2020 – December 2020)

Independent Variables	Unadjusted returns	Unadjusted returns	Risk-adjusted returns	Risk-adjusted returns
CWI	-0.0560*** (0.00176)		-0.00356*** (0.00074)	
CWF		0.02213*** (0.00077)		0.00168*** (0.00054)
Fund-fixed-effect dummy variable	Yes	Yes	Yes	Yes
Time-fixed-effect dummy variable	Yes	Yes	Yes	Yes
Constant	-0.00158 (0.00179)	0.01136*** (0.00108)	0.00372*** (0.00137)	0.00430*** (0.00111)
Obs	3,397	3,239	3,397	3,239
R-sqr	0.8015	0.7325	0.2787	0.2392
F-statistic	59.80	51.36	8.54	8.42

Note. $R_{i,t} = \alpha_i + \beta_1 Cov19_{i,t} + \sum_{t=2}^{t} D_t + \sum_{i=2}^{i} D_i + \upsilon_{i,t}$, Fund unadjusted returns and funds risk-adjusted return are the dependent variables. Independent variables are CWI, CWF, D_t is a set of time fixed-effect dummy variables, and D_i is fund fixed-effect dummy variables. $\upsilon_{i,t}$ is error term. The model is estimated with heteroscedasticity robust standard errors (in parentheses). ***,**,* Represent statistical significance at 1%, 5%, and 10% levels, respectively.

After documenting the negative impact of the COVID-19 outbreak across mutual funds' performance, the study focuses on the success of individual mutual fund managers to alleviate the consequences of this outbreak on fund performance in comparison to the market portfolio (passive investment strategy). This analysis identifies the existence of individual funds that constructed crisis-defensive portfolios. Therefore, the study first tests the impact of the increase in new confirmed cases of COVID-19 on the unadjusted returns of individual mutual funds, and then tests whether this potential impact on individual mutual funds is significantly different from the impact on the returns of the market portfolio (TASI).

The regression model given in Equation (28) is employed to regress TASI returns on *CWI* and to regress mutual fund returns separately on *CWI*. The estimated regression coefficients of each fund are post hoc combined with the estimated TASI regression coefficients using Weesie's (1999) seemingly unrelated regression method. The estimated regression slope of TASI returns on *CWI* is −0.0338 and is significant at the 1% significance level. This slope is used as the benchmark to distinguish the funds with significantly different slopes. The estimated regression slopes of the 79 mutual funds on *CWI* range between −0.00296 and −0.0617, and they are significant at least on the 5% significance level. To identify the funds on which the COVID-19 outbreak had significantly different effects compared with its effects on the market portfolio, the study performs the Wald test of H0: $\hat{\beta}_{fi} = \hat{\beta}_{TASI}$ that rejects the null hypothesis if the Clogg et al. (1995) *Z*-score in Equation (29) is larger than the appropriate χ_1^2 threshold. Table 8.7 summarises the final outcomes on the equality of coefficients. In the table, the number of funds with a slope coefficient that is significantly higher than, not significantly different from, and significantly lower than the slope of the overall market (−0.0338) is stated in the first row, the second row and the third row, respectively.

$$R_t = \alpha + \beta Cov19_t + \varepsilon_t \tag{28}$$

$$Z = \frac{\hat{\beta}_{fi} - \hat{\beta}_{TASI}}{\sqrt{\hat{\sigma}_{fi}^2 + \hat{\sigma}_{TASI}^2}} \tag{29}$$

where R_t is unadjusted returns of the fund and of TASI at week *t*, as calculated using Equation (1), α is the intercept of the model, the independent variable $Cov19$ is *CWI* and ε_t is the error term. $\hat{\beta}_{fi}$ and $\hat{\beta}_{TASI}$ are the estimated regression slopes of the i^{th} fund returns and TASI returns on growth in COVID-19 cases, respectively. $\hat{\sigma}^2_{fi}$ and $\hat{\sigma}^2_{TASI}$ are the standard errors of the estimated slopes, respectively.

Table 8.7

Analysis of the Impact of the COVID-19 Outbreak on Returns of Individual Active Funds (March 2020 – December 2020)

Status	Fund coefficient status	No. of funds	As a percentage of 79
1. Significantly higher	Coef. > –0.0338	3	3.8%
2. No significant difference	Coef. = –0.0338	71	89.8%
3. Significantly lower	Coef. < –0.0338	5	6.4%
Total		79	100%

Note. The table provides the overall outcomes of the Wald test that compares the impact of the COVID-19 outbreak on the market and on the 79 mutual funds in the sample. The number of funds with a slope coefficient that is significantly higher than, not significantly different from, and significantly lower than the slope of the overall market (−0.0338) is stated in the first row, the second row and the third row, respectively. The study considers only a significance level of 5%.

The increase in COVID-19 cases negatively affected the returns of all 79 funds in the sample. The responses of the returns of most mutual funds (71 out of 79) to *CWI* do not significantly differ from the response of the main market portfolio. Consequently, these results reject Hypothesis 5.C that the spread of COVID-19 affected the active mutual funds less than it did the overall market, confirming that the impact on both was similar. The well-diversified holdings of stocks across all industries by most mutual funds may be the reason for this equal negative impact of COVID-19 on the funds and the overall market. Figure 8.2, which illustrates industries' return movement in the Saudi Arabian stock market, shows that there were strong correlations between the returns of most industries during the COVID-19 crisis. It is evident that irrespective of the industries or stocks, COVID-19 brought similar effects on the performance of every investment. In this regard, So et al. (2021) showed that stock returns had higher connectedness during the COVID-19 crisis than during three other crises.

Out of 79 mutual funds, five were able to beat the market in managing the probable negative impact of COVID-19. These funds are mainly invested in essential goods and services industries, such as food production, food and staples retailing, utilities, and healthcare equipment and services. These industries are considered essential in every situation, including pandemics and natural disasters. Therefore, their stocks may not have suffered during the COVID-19 period, unlike those of other industries. Consequently, even without rebalancing their portfolios, such funds could have faced the minimum impact of COVID-19. In addition, actions taken by mutual fund managers could also have reduced the negative impact of COVID-19. This finding indicates that only mutual funds invested in essential services may provide investors with capital-defensive investment options during a pandemic era. Non-essential industries and services were heavily affected by the health measures introduced to mitigate the spread of COVID-19. Three funds that mainly invested in the stocks of energy, commercial and professional services, and real estate management and development companies recorded a significantly higher negative impact than the overall market. The current findings may assist subscribers to mutual funds to allocate their investments during pandemics or similar natural disasters. However, they must also consider their long-term and short-term investment goals. Although mutual funds that excessively invested in non-essential industries were affected more during COVID-19, and those invested in essential industries and services were less affected, the stock market always generously compensates riskier investments.

Figure 8.2

Time-Series Movements of Returns for All Sectors in the Saudi Market (March 2020 – December 2020)

Note. The researchers estimated and analysed the variants in this figure.

8.5 Chapter Summary

The outbreak of COVID-19 has affected economic activities globally, and most financial markets have witnessed severe uncertainty. This study measured the unadjusted return and risk-adjusted performance of actively managed mutual funds during the COVID-19 crisis. On average, mutual funds in Saudi Arabia gained an unadjusted return of 0.414%, which was higher than the unadjusted return for the main market (TASI) of 0.352%. This study is likely the first to apply the FF5FM to measure the risk-adjusted performance of active mutual funds in Saudi Arabia. The model is strongly significant and explains approximately 75% of the variation in equity mutual fund returns. Most importantly, the mutual funds gained a significant positive alpha of 0.15%, which shows their strong performance during the COVID-19 period.

After measuring the performance of active mutual funds, this study used panel data analysis to measure the impact of CWI and CWF on the unadjusted and risk-adjusted return performance of equity mutual funds. The findings suggest that CWI had a significant and negative impact on both returns. However, CWF had a significant and positive impact on unadjusted returns as fatalities seemed to be lesser than expectations. Further, only a few mutual funds provided investors with capital-defensive investment options during the pandemic and focused their investments on the sectors that provide essential goods and services, including food production, food and staples retailing, utilities, and healthcare equipment and services.

Chapter 9: Conclusion and Limitations of the Study

9.1 Introduction

This chapter concludes the investigation of mutual fund performance, performance persistence and the impact of unprecedented factors on fund performance in Saudi Arabia. In the preceding four chapters (Chapter 5 – Chapter 8), the research findings and discussions have been presented. Chapter 5 involved comprehensive investigations of mutual fund performance in Saudi Arabia. In Chapter 6, mutual fund performance persistence (existence of genuine fund managers' skills) has been assessed. Chapter 7 has explored the influence of investor sentiment along with oil price volatility and fund-specific factors on the performance of mutual funds in Saudi Arabia, whereas Chapter 8 has investigated the impact of COVID-19 on the unadjusted and risk-adjusted return performance of active mutual funds in Saudi Arabia. This chapter brings together the conclusions of the previous four chapters. It describes how the research objectives have been fulfilled and provides comprehensive answers to the research questions discussed in Chapter 1. In addition, it explores the implications and limitations of this study while offering valuable suggestions for future research endeavours.

The remainder of this chapter is organised as follows: The subsequent section presents the objectives of the study and discusses the key findings. Section 9.3 describes this study's contributions to the existing body of knowledge and presents concluding remarks. Section 9.4 critically addresses the limitations of the study. The last section identifies areas that warrant further investigation.

9.2 Research Objectives, Key Findings and Concluding Remarks

This section addresses the five main research objectives and their related hypotheses on mutual funds in Saudi Arabia, which were presented in Chapter 1. Some questions have been subdivided, to enhance the clarity of the findings. This section summarises the answer to each of those questions and discusses the study's findings in light of those of other studies.

9.2.1 Efficiency of Mutual Fund Performance Measuring Models

The first research objective is to rank asset pricing models and identify the most efficient model that measures active mutual fund risk-adjusted performance in Saudi Arabia. To fulfil this objective, the study subdivided the first research question into three sub-questions and the related three sub-hypotheses that were examined in Chapter 5.

The first sub-question (1.A) asks: Do multi-factor pricing models (FF3FM, FF5FM, FFC4FM and FFC6FM) measure the performance of active mutual funds more accurately than the SFM? Accordingly, Hypothesis 1.A assumes that the multi-factor models explain the returns of active funds better than the SFM. To examine this hypothesis, the study applied the GRS *F*-statistic test, GRS *J*-statistic test and MAA to rank the tested models. The results of the GRS *F*-statistic test along with those of the other tests suggested that the multi-factor models explain active mutual fund return better than the SFM.

The second sub-question (1.B) is as follows: Does the FF5FM measure the performance of active mutual funds more accurately than the FF3FM? Thus, Hypothesis 1.B assumes that the FF5FM explains the returns of active funds better than the FF3FM. The GRS *F*-statistic test, GRS *J*-statistic test and MAA were applied to rank the competing models. The analysis results showed that FF5FM has better explanatory power of active mutual fund return than the preceding FF3FM.

Last, the third sub-question (1.C) is as follows: Does the FFC6FM measure the performance of active mutual funds more accurately than the FFC4FM? Consequently, Hypothesis 1.C assumes that the FFC6FM explains the returns of active funds better than the FFC4FM. The GRS *F*-statistic test, GRS *J*-statistic test and MAA were applied to rank the competing models. The findings showed that the FFC6FM explains the returns of active funds better than the preceding FFC4FM.

Overall, from the previous ranking of the models, the FFC6FM emerges as the most efficient model for explaining the returns of active funds in Saudi Arabia. The current findings align with those of prior studies that have examined asset pricing models in the context of portfolios that comprise cross-section stock returns (Chiah et al., 2016; Fama & French, 2015, 2017, 2018; Foye, 2018). This study emphasises the relationship between mutual fund returns and systematic risk factors, such as the market, size, value, profitability, investment and momentum risk factors. The current findings highlight the significance of adjusting the mutual funds' returns against these factors when measuring the risk-adjusted performance of Saudi mutual funds. Consequently, when incomplete models are employed, they fail to account for these risks in measuring mutual fund performance and may lead to an overestimation of the actual risk-adjusted return performance of the mutual fund.

9.2.2 Mutual Fund Return Performance in Saudi Arabia

The second research objective is to conduct a comprehensive investigation of active and passive mutual fund performance in Saudi Arabia. This objective has been subdivided into five sub-objectives, all of which were fulfilled in Chapter 5. The sub-objectives and their sub-hypotheses are discussed next.

9.2.2.1 Benchmark-Adjusted Performance and Risk-Adjusted Performance

The first sub-objective is to investigate the benchmark-adjusted and risk-adjusted performance of active and passive funds. To accomplish this objective, the study poses the first sub-question (2.A), about the extent to which active and passive funds in Saudi Arabia perform against three different benchmark indices: TASI, MSCI-SADI and S&P-SADITR. To address sub-question (2.A), four hypotheses have been developed: While Hypotheses 2.A and 2.D were developed to examine the benchmark-adjusted performance of active and passive funds, respectively, Hypotheses 2.H and 2.K were developed to examine the risk-adjusted performance of active and passive funds, respectively.

9.2.2.1.1 Benchmark-Adjusted Performance

Hypothesis 2.A assumes that the unadjusted return of active funds differs significantly from the unadjusted market return, and Hypothesis 2.D assumes that the unadjusted return of passive funds differs significantly from the unadjusted market return. To test these hypotheses, the mean-difference measure was used to assess benchmark-adjusted performance. Overall, the results showed that active mutual funds significantly outperformed the market. The present findings align with Al Rahahleh and Bhatti's (2022) findings, indicating a positive and significant mean difference against TASI for active funds. This contrasts with the studies conducted by BinMahfouz and Hassan (2012), Merdad et al. (2010), Omri et al. (2019) and Zouaoui (2019), which did not identify a significant difference between the unadjusted returns of active funds and the market's unadjusted returns. Conversely, the present study found no evidence of a significant difference between passive fund unadjusted returns and market unadjusted returns. This finding indicates that passive funds track their benchmark indices very closely. Significantly, this is maybe the first study to examine the benchmark-adjusted performance of passive funds in Saudi Arabia.

9.2.2.1.2 Risk-Adjusted Performance

Hypothesis 2.H assumes that active funds generate positive and significant risk-adjusted performance (alpha). Similarly, Hypothesis 2.K assumes that passive funds generate positive and significant risk-adjusted performance (alpha). To examine these hypotheses, the FFC6FM and the SFM were applied to estimate this performance of active and passive funds, respectively. The analysis results showed that active mutual funds exhibited significant outperformance compared with the market. The current findings align with those of Al Rahahleh and Bhatti (2022) as well as of Omri et al. (2019), who identified the outperformance exhibited by active funds. In contrast, the present study did not find discernible evidence of the significant outperformance of passive funds. The observed results indicate a non-significantly negative alpha for passive funds. This finding aligns with expectations, considering that the primary objective of passive funds is to closely track the returns and risks associated with their benchmark indices, rather than to outperform them.

9.2.2.2 Performance Variation Between Overall Sample and Subsamples

The second sub-objective is to compare the performance of active and passive funds during SMEs with their performance in the overall sample period. To achieve this objective, the study poses the second sub-question (2.B), which investigates how active and passive funds performed during SMEs compared with their performance in the overall sample period. To address this sub-question, four hypotheses were developed: Hypotheses 2.B and 2.E were developed to examine the performance variation during SMEs against the overall sample period based on the benchmark-adjusted performance of active and passive funds, respectively. Moreover, Hypotheses 2.I and 2.L were developed to examine the performance variation during SMEs and the overall sample period based on the risk-adjusted performance of active and passive funds, respectively.

9.2.2.2.1 Based on Benchmark-Adjusted Performance

Hypothesis 2.B assumes that the benchmark-adjusted performance of active funds varies during SMEs than during the overall sample period. Likewise, Hypothesis 2.E assumes that the benchmark-adjusted performance of passive funds varies during SMEs than during the overall sample period. After measuring this performance for the overall sample period and each SME, a one-sample *t*-test was conducted to determine significant differences between the two sample periods. The results revealed that the benchmark-adjusted performance of active funds during financial crises and bearish (and bullish) market conditions were significantly higher (lower) than their performance during the overall sample period. This finding indicates that active fund managers' strategies may respond differently to SMEs, leading to varying degrees of outperformance or underperformance compared with their benchmark indices. These findings support those of Al Rahahleh and Bhatti (2022) who found significant higher benchmark-adjusted performance for active funds during low-market-volatility periods. Conversely, passive funds generally exhibited similar benchmark-adjusted performance during the overall sample period and SMEs.

9.2.2.2.2 Based on Risk-Adjusted Performance

Hypothesis 2.I assumes that the risk-adjusted performance of active funds varies during SMEs than during the overall sample period. Likewise, Hypothesis 2.L assumes that the risk-adjusted performance of passive funds varies during SMEs than during the overall sample period. After estimating alpha's coefficients for each SME and for the overall sample period, the Wald test was conducted to examine whether the difference between estimated alphas significantly deviates from zero. A significant (non-significant) result from this test indicates that the risk-adjusted return performance during SMEs significantly varies (does not vary) from that during the overall sample period.

The results showed that the risk-adjusted performance of active funds for the period before the 2015 financial reforms was significantly higher than their performance during the overall sample period. This finding suggests that the introduction of financial reforms brought about changes in the performance of active funds, possibly influencing their risk sensitivity and investment decisions. Importantly, the results also have strong economic significance since the difference in performance reaches up to 4.4% per year. In general, these empirical findings align with those of Kosowski (2011) and Moskowitz (2000) that the risk-adjusted performance of active funds can exhibit greater variability during certain SMEs compared with the overall sample period. Drawing from this finding, investors may capitalise on the fluctuating nature of active fund performance by incorporating predictability into their strategies. They would increase their investments during favourable periods while avoiding investing in certain times. Conversely, passive funds demonstrated a different pattern. Generally, the risk-adjusted performance of passive funds was similar during SMEs and the overall sample period. This finding emphasises their strategy of closely tracking their benchmark indices at all times, resulting in consistent performance regardless of SMEs.

9.2.2.3 Comparison Between Performance of Active and Passive Funds

The third sub-objective is to compare the performance of active funds to that of passive funds. To attain this objective, the third sub-question (2.C) was as follows: To what extent did active funds perform compared with passive funds? To answer this sub-question, Hypotheses 2.G and 2.N have been developed based on benchmark-adjusted performance and risk-adjusted performance, respectively.

Hypothesis 2.G assumes that the benchmark-adjusted performance of active funds differs significantly from that of passive funds. After measuring the performance of active and passive funds, two-sample *t*-tests were conducted to identify significant differences between the benchmark-adjusted performance of active and passive funds. Likewise, Hypothesis 2.N assumes that the risk-adjusted performance (alpha) of active funds significantly differs from that of passive funds. To standardise the comparison, the risk-adjusted performance of all funds was estimated by using both the SFM and the FFC6FM, and then, the Wald test was used to check for significant differences between the estimated alpha coefficients of active and passive funds.

Overall, using both approaches, the benchmark-adjusted performance and risk-adjusted performance, the results showed statistically significant higher performance of active mutual funds compared with the performance of passive funds. In essence, even after adjusting for the additional risks of active funds, they still can outperform passive funds. The current findings contradict with those of studies on developed markets that are believed to be more efficient (Crane & Crotty, 2018; Pace et al., 2016), and correspond with the findings of other studies on emerging markets (Shreekant et al., 2020). The current findings suggest that an active investment strategy is likely to be more effective than a passive investment strategy in the Saudi equity market.

9.2.2.4 Performance Variation Across Benchmark Indices

The fourth sub-objective is to explore the potential impact of selecting different benchmark indices as proxies for market returns on the inference of mutual fund performance. To fulfil this objective, the fourth sub-question (2.D) asks: Does the selection of a benchmark index as a proxy of market return change the inference of mutual fund performance? To address this sub-question, four hypotheses have been developed: Hypotheses 2.C and 2.F were developed to investigate this sub-question based on the benchmark-adjusted performance of active and passive funds, respectively. Moreover, Hypotheses 2.J and 2.M were developed to examine this sub-question based on the risk-adjusted performance of active and passive funds, respectively.

9.2.2.4.1 Based on Benchmark-Adjusted Performance.

Hypothesis 2.C supposes that the inference of the benchmark-adjusted return performance of active funds varies when using different market return proxies. Likewise, Hypothesis 2.F assumes that the inference of the benchmark-adjusted return performance of passive funds varies when using different market return proxies. After measuring such performance using different proxies of market returns, a one-sample *t*-test was employed to examine for significant difference between the measurements. The findings indicate a significant difference in benchmark-adjusted performance when measured using different indices, specifically, TASI and S&P-SADITR.

9.2.2.4.2 Based on Risk-Adjusted Performance

Hypothesis 2.J assumes that the inference of the risk-adjusted return performance of active funds varies when using different market return proxies. Similarly, Hypothesis 2.M postulates that the inference of the risk-adjusted return performance of passive funds varies when using different market return proxies. To examine these hypotheses, first, the risk-adjusted performance of these funds against different market proxies was estimated. Then, the Wald test was used to identify significant difference between measured performance. The findings show a significant difference in risk-adjusted performance when measured using TASI and S&P-SADITR.

9.2.2.4.3 Overall Conclusion About Performance Variation Across Benchmark Indices

The overall findings suggest that the choice of the benchmark index can lead to a notable shift in the interpretation of mutual fund performance. Specifically, when the same benchmark index is used, different performance measures, such as the benchmark-adjusted performance and risk-adjusted performance, tend to yield similar conclusions. However, when different benchmark indices are employed, the inferences drawn from the same performance measure can diverge. This observation corresponds with the findings of Grinblatt and Titman (1994) regarding US mutual funds. The current results maybe provide the first evidence of the significant impact that selecting a market return proxy can have on the interpretation of mutual fund performance.

9.2.2.5 Market Timing Ability of Fund Managers

The fifth sub-objective is to examine the market timing skills of active fund managers. To achieve this objective, the fifth sub-question (2.E) asks: To what extent can active mutual funds in Saudi Arabia time the market? To answer this sub-question, Hypothesis 2.O has been developed, which assumes that active mutual funds possess significant market timing skills. The study employed two key models to assess fund managers' market timing ability—the Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model—in their original forms and within the framework of the FFC6FM.

The Treynor and Mazuy (1966) model and the Henriksson and Merton (1981) model both consistently revealed that active mutual funds in Saudi Arabia possess stock selectivity skills but lack market timing skills. This is evidenced by the consistently negative and significant market timing coefficients observed in both models. These findings are in line with those of Merdad et al. (2016) and Zouaoui (2019). However, several explanations are proposed for these results in the Saudi Arabian context. These include the possibility of mutual fund managers inaccurately anticipating market movements, the impact of high transaction costs by following market fluctuations, and the potential perverse timing behaviour stemming from a focus on stock selectivity over market timing.

Furthermore, asymmetric correlation phenomena may influence stock markets, particularly during bearish market periods. The higher sensitivity of fund returns to market returns during market downturns suggests that the negative market timing coefficients might be linked to an asymmetric correlation phenomenon in the Saudi Arabian stock markets. However, to the best of our knowledge, there is currently no empirical evidence in the existing literature of Saudi Arabia about asymmetric correlation phenomena to supports this assumption.

9.2.3 Active Fund Performance Persistence (Managerial Skills)

In Chapter 6, the third research objective attempts to examine the risk-adjusted performance persistence of individual active funds, that is, whether their risk-adjusted return performance can be attributed to managerial skills or pure luck. To fulfil this objective, the third research question is as follows: Does the risk-adjusted return performance of individual active mutual funds persist in the Saudi market? Accordingly, Hypothesis 3.A conjectures that managerial skills do exist among a group of active equity mutual funds. Furthermore, Hypotheses 3.B and 3.C have similar assumptions for the subsample periods pre and post the 2015 financial reforms, respectively.

The study employed the bootstrap statistical technique to examine the proposed hypotheses. This approach involved comparing the actual cross-section of t-statistic estimates of funds' alphas with results obtained from bootstrap simulations. To execute this approach, the study computed the t-statistic estimates of alphas for each individual fund in both the actual data and the results obtained from bootstrap simulations. These estimates were then organised in ascending order, creating two distinct cross-sections: one comprising the actual t-statistic estimates of alphas and the other consisting of those derived from bootstrap simulations. Subsequently, these ordered cross-sections were divided into selected percentiles. Within the extreme right tail of the cross-section distributions, if the actual t-statistic estimates of alphas are above those from bootstrap simulations (the luck distribution), it can be inferred that luck alone is not the sole source of significant positive alphas, and genuine investment skills exist.

Analysing Hypothesis 3.A, the study found that active mutual funds demonstrating superior performance consistently outperformed the market from January 2010 to December 2020. The results in Table 6.7 show that actual t-statistic estimates of alphas surpassed those generated by bootstrap simulations, particularly at the 80th percentile and above. This finding confirms that funds positioned in the top 20% in terms of returns possess genuine managerial skills, thereby supporting the hypothesis that genuine managerial skills do indeed exist. Hypothesis 3.B examines the performance persistence focusing on the period before the 2015 financial reforms (January 2010 – June 2015). For this span, the study observed remarkable superior performance persistence among active mutual funds. In Table 6.8, the actual t-statistic estimates of alphas exceed those generated by the bootstrap simulations at the 40th percentile and above, meaning that funds that fall in the 40th percentile and above persistently outperformed the market. Contrasting results were found when analysing Hypothesis 3.C, which examines performance persistence for the period after the 2015 financial reforms (July 2015 – December 2020). The results in Table 6.9 reveal that actual t-statistic estimates of alphas surpassed those generated by the bootstrap simulations at the 99th percentile and above, indicating that mutual funds positioned only in the top 1% in terms of returns persistently outperformed the market during this period.

Generally, these findings suggest an increased prevalence of skilled managers in Saudi Arabia in comparison to findings on developed markets. Notably, the present findings show that skilled managers exist within the 80th percentile and above in Saudi Arabia, whereas in developed markets, their presence is predominantly confined to the upper group of outperforming funds, specifically within the 90th percentile and above (Cuthbertson et al., 2008; Kosowski et al., 2006).

Consequently, it can be inferred that a more substantial cohort of skilled managers may be observable in emerging markets, contrasting with their counterparts in developed markets. In essence, the current findings carry profound implications for market efficiency, as the existence of mutual fund managers consistently outperforming the market during the overall sample period implicitly challenges the EMH.

However, there was a significant decline in the number of mutual funds exhibiting persistent superior performance after the implementation of the 2015 financial reforms. The current findings of the subsample analyses are consistent with those of Kosowski et al. (2006), who also subdivided their sample from the US into two subsamples: one for the 1975–1989 period, and the other for the 1990–2002 period.[46] They found that outperforming fund managers have become fewer since 1990. They suggested that the reduction in the number of outperforming fund managers could be attributed either to an increase in the market efficiency or to fierce competition among the large number of new funds or perhaps both. The most likely reason for a reduction in the number of superior funds in Saudi Arabia is the liberalisation of the Saudi stock market, which has improved the stock price discovery process (valuation) and the ask–bid spreads (liquidity) and has decreased high–low price volatility (Sharif, 2019). The findings of the present study and those of Kosowski et al. (2006) for the US highlight a shared trend of severe decline in the number of funds demonstrating superior performance following financial reforms.

9.2.4 Impact of Investor Sentiment on Equity Mutual Fund Performance

The fourth research objective is to investigate the potential influence of investor sentiment on unadjusted performance and risk-adjusted performance of mutual funds. This objective is

[46] During this era, the US equity market experienced several legislative changes aimed at enhancing market efficiency, including Market-Wide Circuit Breakers (1988), Regulation ATS (Alternative Trading Systems) (1998), Order Handling Rules (1997), Market Fragmentation and SEC Rule 11Ac1-7 (1997), Regulation FD (Fair Disclosure) (2000), the Sarbanes–Oxley Act (2002), and Decimalization (2001).

particularly pertinent in the context of the Saudi equity markets, where individual traders significantly shape the daily trading. While they contribute between 5% and 10% of the total trading volume in developed markets (Adinarayan, 2021), in the Saudi equity market, this figure rises dramatically to an average of 82% of monthly trading volume between 2010 and 2020 (Tadawul, 2020). This pronounced involvement of individual traders underlines their substantial role in the Saudi market.

Notably, investor sentiment, commonly utilised as an indicator of the noisy expectations of individual traders, has a significant impact on the returns and volatility of the Saudi equity market (Alnafea & Chebbi, 2022; Altuwaijri, 2016). Despite the fact that the performance of mutual funds varies from the overall market performance owing to the expertise of professional managers, investor sentiment may influence mutual fund performance in the Saudi market, given the dominant role of individual traders in this market. Building upon earlier studies that have identified the influence of investor sentiment on the returns and volatility of the Saudi main equity market, and recognising the direct and exclusive investment of Saudi equity mutual funds in this market, it is possible that investor sentiment could extend its influence to mutual fund performance.

The study poses the fourth research question to achieve the fourth research objective regarding whether the performance of active and passive funds in the Saudi market is affected by investor sentiments. Consequently, Hypothesis 4.A assumes that investor sentiment positively affects active and passive fund unadjusted performance. Furthermore, Hypothesis 4.B supposes that investor sentiment positively affects active and passive fund risk-adjusted performance. To examine these hypotheses in Chapter 7, the study employed panel data regressions, which is a robust method for estimating the influence of investor sentiment on fund performance. The study used five proxies for investor sentiment: trading volume, market turnover, average P/E ratio, bull–bear ratio and IPCSI-SA.

The study examined the impact of investor sentiment on both unadjusted and risk-adjusted returns of active and passive mutual funds, independently and with fund-specific factors. For active funds, the findings indicate a consistent positive impact of all sentiment proxies on unadjusted returns, signifying that investor behaviour contributes to higher unadjusted returns for active mutual funds. In terms of risk-adjusted returns, active funds consistently showed a positive relationship with sentiment proxies, suggesting that fund managers can exploit sentiment-driven anomalies for better performance. These findings oppose the EMH and highlight the role of sentiment-driven anomalies in driving fund performance.

For passive funds, only trading volume demonstrated a consistent significant influence on both unadjusted and risk-adjusted returns. This can be attributed to the passive nature of these funds, which aim to replicate market performance rather than capitalise on sentiment-driven opportunities. Overall, these findings add evidence of the influence of investor sentiment on mutual fund performance to that provided by studies that proved investor sentiment influences the main market returns and volatility (Alnafea & Chebbi, 2022; Altuwaijri, 2016).

9.2.5 Impact of COVID-19 on Mutual Fund Performance in Saudi Arabia

The fifth research objective aims to investigate the potential effects of the COVID-19 outbreak on both the unadjusted performance and risk-adjusted performance of active funds in Saudi Arabia. The unprecedented wide-ranging economic repercussions of the COVID-19 pandemic have disrupted normal operations in all economic sectors. The Government of Saudi Arabia introduced measures to counter the spread of this pandemic, such as tightening or easing human movement and lockdowns, depending on whether there were new confirmed cases. These measures have had a significant and negative impact on the performance of the stock market (Alzyadat & Asfoura, 2021; Atassi & Yusuf, 2021; Sayed & Eledum, 2021). Although active mutual fund performance could vary from the performance of the stock market, a potential effect of the COVID-19 spread on mutual fund performance remains. Therefore, the study raised the fifth research question: Did the COVID-19 outbreak affect the unadjusted return performance or the risk-adjusted return performance of active mutual funds? Subsequently, Hypothesis 5.A assumes that increases in COVID-19 new cases and in COVID-19 fatalities negatively affect active mutual fund unadjusted return performance, and Hypothesis 5.B assumes that such increases negatively affect active mutual fund risk-adjusted return performance.

To examine these hypotheses in Chapter 8, the study employed panel data regressions for measuring the influence of the COVID-19 pandemic on fund performance. The empirical findings showed a significant and negative impact of the increase in weekly new infections on both the unadjusted return performance and risk-adjusted return performance of active mutual funds. This significant and negative association could have resulted from the counter-asset choices made by the fund managers to overcome the negative effects of COVID-19. It is evidence of the low resilience in mutual fund performance to the economic restrictions associated with the spread of COVID-19. The current findings are consistent with those of Alzyadat and Asfoura (2021) and Atassi and Yusuf (2021), who measured the impact of the COVID-19 outbreak on the Saudi main market index and sector indices.

9.3 Practical Contribution and Policy Recommendations

The implications drawn from this thesis extend across various practical domains, underscoring its contributions to investment decision-making processes. Specifically, these practical contributions hold particular significance for three key stakeholder groups: mutual fund investors, fund managers and policymakers.

9.3.1 Practical Contribution

Primarily, the findings derived from this study would provide valuable assistance to mutual fund investors, aiding them in their investment planning and analytical endeavours. The first finding of this study highlights the efficiency of FFC6FM in precisely estimating the performance of active funds. Investors can confidently employ this more accurate, comprehensive model to estimate the mutual fund performance, as it captures the various sources of risk to which mutual funds are exposed more effectively. Additional findings from this study underscore distinct behaviours in mutual fund performance within SMEs, the performance of active funds in comparison to passive funds, and the market timing skills of fund managers. These findings offer investors valuable information for their decision-making processes in investment.

In addition, the findings hold considerable importance for mutual fund providers as they shape their product portfolios and investment strategies. In light of the current findings of the positive and significant relationship between fund size and fund performance, fund providers may consider merging smaller funds under their management into larger entities as a strategy to enhance overall performance. Other findings from this study include the significant underperformance and outperformance of mutual funds during different SMEs and the failure to mitigate the adverse influence of COVID-19 on the returns of active funds. These results should prompt fund providers to review the reasons for their underperformance during certain SMEs and to endeavour to understand the reason they could not mitigate the impact of the COVID-19 pandemic on their funds.

9.3.2 Policy Recommendations

In the scope of policy development, this study holds the potential to serve policymakers as they undertake regulatory attempts and oversight operations, which, in turn, reinforce the stability and sustained growth of the mutual fund industry. Subsequently, this study suggests these valuable regulatory recommendations:

- Standardisation of Reporting Fund Performance

Based on the results obtained in responding to the initial research question, the study recommends the standardisation of reports on the performance of active mutual funds. In Saudi Arabia, each provider of active mutual funds currently reports their funds' performance using specific measures, such as the mean-difference measure, the SFM or, in some cases, the FF3FM. The study has demonstrated that utilising inappropriate models, which fail to account for all risk factors when estimating active fund risk-adjusted returns, may lead to an overestimation of performance. To address this issue, the SACMA should obligate fund providers to disclose performance using the best model identified by this study: the FFC6FM. Alternatively, providers could be required to report using all major pricing models, including the SFM, FF3FM, FF5FM, FFC4FM and FFC6FM. The standardisation of reporting in this manner would enable investors to make fair comparisons between different funds.

- Strengthening Benchmarking Governance

Considering the findings gathered from addressing Question 2.D, this study proposes that the SACMA take measures to oversee the utilisation of indices in adjusting fund performance as reported by fund providers. Specifically, the practice of employing an index with a price-level methodology to adjust the performance of a fund that accumulates dividends can result in misleading outcomes. In such instances, the adjusted returns of the fund may appear higher than their actual value. Therefore, it is recommended that the SACMA require fund providers to employ a suitable benchmark index when reporting adjusted fund performance.

- Enhancing Transparency

The findings of the study that reveal a significant and persistent outperformance of active funds compared with the market pose a challenge to the assumption of market efficiency. These findings raise questions about this significant and persistent outperformance. In response to this issue, SACMA should enhance transparency by requiring fund managers to disclose their past stock holdings and the dates of purchase and sale.

- Providing more Metrics of Investor Sentiment

Several studies have illustrated the influence of investor sentiment on the returns and volatility of the overall stock market (Alnafea & Chebbi, 2022; Altuwaijri, 2016). This study contributes to this literature by offering empirical evidence that highlights the significant impact of investor sentiment on mutual fund performance, reinforcing its crucial role in capital markets. Despite the acknowledged importance of investor sentiment, there remains a deficiency in the proxies of investor sentiment that reflect its pivotal role within capital markets. To address this gap, this study recommends the development of diverse indices to measure investor sentiment.

9.4 Limitations of the Study

9.4.1 Data Availability

The mutual fund industry in Saudi Arabia is still in its nascent stages, especially when compared with its counterparts in well-established markets, such as the US. Specifically, this study explores passive mutual funds within Saudi Arabia, encompassing a total of 14 funds that have existed over time. However, it is important to note that a performance persistence analysis of passive funds could not be undertaken in Chapter 6 because of the limited sample size, which hindered the ability to arrive at enough conclusive cross-sectional t-statistic estimates of alphas. This limitation persisted in Chapter 8, in which the analysis of passive funds was constrained by the availability of only six such funds during the given analytical time frame. Further, it is crucial to approach the analysis of passive funds and the interpretations of the findings in Chapters 5 and 7 with a high degree of caution. Nonetheless, the utilisation of the complete set of 14 available funds underscores this study's commitment to rigor and comprehensiveness within the confines of the available data.

9.4.2 Limited Variables

The study's exploration of variables is restricted by the limited data at hand. To illustrate, Saudi Arabian mutual funds refrain from disclosing crucial information, such as past trading transactions and the corresponding values. If these data were accessible, it would empower researchers to investigate other aspects further, such as the skills of mutual fund managers and other factors that likely influence mutual fund performance, including portfolio turnover. Similarly, the proxies of investor sentiment present another instance. As discussed in the literature review in Chapter 3, a multitude of proxies are available for gauging investor sentiment. Unfortunately, the present investigation was confined by data constraints, allowing this study to examine only the influence of five investor sentiment proxies on the performance of Saudi Arabian mutual funds.

9.4.3 Temporal Scope of the Study

Diverging from research studies that encompass an extensive 40- to 60-year evaluation of mutual fund performance in developed markets, this study's analytical time frame unfolds across 11 years, ranging from January 2010 to December 2020. It is worth noting that the Saudi Arabian mutual fund landscape remains comparatively nascent, contributing to the limitation of the analysis duration. Within this temporal span, this study meticulously scrutinised a robust sample size of 120 active and 14 passive funds. Further, before 2010, the mutual fund industry exhibited limited participation, with only a handful of funds in existence.

9.5 Suggestions for Future Research

This subsection identifies areas that warrant further investigation. It suggests potential avenues for future research that could build upon the current study's limitations and contribute to the continued advancement of knowledge in this field.

First, this comprehensive analysis of mutual fund performance has been undertaken during the relatively early phases of the Saudi mutual fund industry. Currently, the market is still undergoing continuous regulatory adjustments and transformative reforms. Further, the mutual fund industry is growing rapidly. Accordingly, a further investigation into mutual fund performance is warranted once the industry reaches a state of greater maturity. Specifically, in the future, there could be a more representative sample of passive funds to generalise for the passive investment strategy.

In addition, this study possesses the potential for expansion to encompass the GCC countries. The populations of these nations not only share analogous beliefs, traditions and behaviours, but also possess the liberty to invest in any of the GCC equity markets. Consequently, the outcomes regarding the impact of investor sentiment on mutual fund performance within this study hold the promise of regional generalisation, extending beyond the confines of the Saudi Arabian market. To enhance the robustness of such an extension, a comprehensive cross-country comparison of the influence of investor sentiment on mutual fund performance could be undertaken, taking into account unique market dynamics and regulatory landscapes across the GCC region.

Last, gaining access to the portfolio holdings of mutual funds would represent a significant stride towards conducting meticulous investigations into the skill of fund managers. Although the bootstrap statistical technique in Chapter 6 has shown that fund managers' skills do not persist because of good luck, an analysis of mutual fund portfolio holdings, especially during SMEs, would provide better understanding of their capabilities. Such an analysis would illuminate the intricate interplay between managerial decision-making regarding asset allocation and the resultant performance of mutual funds.

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Appendices

Appendix A

The differences between active funds and passive funds

Active funds	**Passive funds**
Conduct rigorous fundamental analysis and technical analysis to identify under/over-valued stocks, or time the market.	Replicate the market returns and risks. They just update the portfolio according to market index maintenance.
Aim to outperform the market	Aim to perform as the market
Higher management fee	Lower management fee
Pay higher taxes	Lower taxes
Traded after-market closure directly with issuers in the primary market at their net asset value.	Mutual index funds traded after-market closure directly with issuers in the primary market at their net asset value. However, ETFs cab be traded intraday in secondary markets.
Less transparency	Disclose their holdings (transparency)

Note. The Appendix summarises the differences between active and passive funds.

Appendix B

The efficiency tests of SFM, FF3FM, FF5FM, FFC4FM, and FFC6FM to explain monthly excess returns of mutual funds

	TASI benchmark			MSCI benchmark			S&P benchmark		
	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|
Panel A: 9 portfolios Market-SMB									
SFM	1.99029	19.23422	0.00329	2.06108	19.91851	0.00302	1.09549	10.58734	0.00136
FF3FM	1.91313	18.79905	0.00318	1.90803	18.74905	0.00281	1.05152	10.33279	0.00134
FF5FM	1.66755	16.66578	0.00288	1.65892	16.57953	0.00247	0.89556	8.95059	0.00111
FFC4FM	1.66131	16.46435	0.00302	1.65279	16.37991	0.00275	0.92295	9.14726	0.00116
FFC6FM	1.49595	15.08020	0.00281	1.48395	14.95930	0.00248	0.82324	8.29915	0.00099
Panel B: 9 portfolios Market-HML									
SFM	1.66604	16.10072	0.0033	1.58642	15.33128	0.00302	0.73169	7.071394	0.00123
FF3FM	1.69759	16.68114	0.00311	1.53714	15.10454	0.00272	0.78409	7.704971	0.00109
FF5FM	1.48159	14.80725	0.00280	1.32802	13.27251	0.00237	0.68161	6.81230	0.00088
FFC4FM	1.52494	15.1128	0.00294	1.37300	13.60707	0.00266	0.71319	7.06839	0.00087
FFC6FM	1.37666	13.8776	0.00272	1.22762	12.37529	0.00238	0.64840	6.53661	0.00075
Panel C: 9 portfolios Market-RMW									
SFM	2.14105	20.69120	0.00332	1.85503	17.92718	0.00305	1.43439	13.86262	0.00156
FF3FM	2.58509	25.40201	0.00321	2.19777	21.5961	0.00283	1.79063	17.59576	0.00157
FF5FM	2.31013	23.08781	0.00294	1.92221	19.21088	0.00253	1.55125	15.50382	0.00139
FFC4FM	2.35316	23.3208	0.00309	1.99865	19.80756	0.00281	1.63639	16.21816	0.00147
FFC6FM	2.17617	21.93725	0.00288	1.81241	18.27041	0.00256	1.47746	14.89451	0.00135
Panel D: 9 portfolios Market-CMA									
SFM	2.20330	21.29280	0.00303	1.91369	21.29280	0.00303	1.22836	11.87145	0.00112
FF3FM	2.24833	22.09287	0.00295	1.98110	19.46697	0.00256	1.31730	12.94455	0.00113
FF5FM	2.21553	22.14233	0.00265	1.96092	19.5977	0.00222	1.46216	14.61337	0.00099

	TASI benchmark			MSCI benchmark			S&P benchmark		
	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|
FFC4FM	2.03886	20.20601	0.00281	1.80903	17.92834	0.00253	1.24065	12.29597	0.00107
FFC6FM	2.04151	20.57978	0.00259	1.81475	18.29403	0.00226	1.37199	13.83123	0.00097
Panel E: 9 portfolios Market-MOM									
SFM	3.06766	29.6459	0.00301	2.54798	24.62388	0.00275	2.08549	20.15511	0.00123
FF3FM	2.96218	29.1073	0.00295	2.42979	23.87600	0.00258	2.03960	20.04228	0.00128
FF5FM	2.76287	27.61251	0.00266	2.28365	22.82313	0.00229	1.98369	19.82576	0.00117
FFC4FM	2.63478	26.11184	0.00282	2.16129	21.41941	0.00255	1.79199	17.76020	0.00103
FFC6FM	2.51459	25.34874	0.00260	2.07316	20.8989	0.00229	1.77592	17.90326	0.00098
Panel F: 9 portfolios SMB-HML									
SFM	2.18789	21.14384	0.00333	2.12840	20.56909	0.00305	1.09789	10.61054	0.00129
FF3FM	2.20866	21.70310	0.0032	2.02412	19.88972	0.00282	1.15405	11.34033	0.00122
FF5FM	1.98174	19.80581	0.00292	1.78948	17.88438	0.00249	1.07182	10.71216	0.00105
FFC4FM	2.01298	19.94945	0.00306	1.85444	18.37835	0.00278	1.14013	11.29974	0.00117
FFC6FM	1.85803	18.73022	0.00285	1.69123	17.0487	0.00252	1.08611	10.94922	0.00108
Panel G: 9 portfolios SMB-RMW									
SFM	2.26555	21.89436	0.00311	2.12919	20.57668	0.00282	1.38981	13.43179	0.00131
FF3FM	2.18348	21.45569	0.00299	2.02771	19.92499	0.00260	1.34934	13.25936	0.00125
FF5FM	2.11637	21.15130	0.00267	1.95315	19.52010	0.00223	1.46217	14.61349	0.00111
FFC4FM	1.9059	18.8892	0.00285	1.76482	17.49024	0.00257	1.14619	11.35981	0.00102
FFC6FM	1.89405	19.0932	0.00261	1.73999	17.54032	0.00227	1.26759	12.77876	0.00095
Panel H: 9 portfolios SMB-CMA									
SFM	2.33580	22.57331	0.00286	2.54967	24.64027	0.00257	1.14544	11.07012	0.00094
FF3FM	2.47199	24.29063	0.00272	2.64800	26.02022	0.00233	1.28409	12.61824	0.00089
FF5FM	2.48236	24.80903	0.00238	2.63107	26.29533	0.00198	1.44301	14.42206	0.00078
FFC4FM	2.22144	22.01542	0.00252	2.35906	23.37941	0.00223	1.19019	11.79587	0.00074
FFC6FM	2.26724	22.85524	0.00227	2.39028	24.09578	0.00193	1.31684	13.27524	0.00070

	TASI benchmark			MSCI benchmark			S&P benchmark		
	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|
Panel I: 9 portfolios SMB-MOM									
SFM	3.92298	37.91185	0.00317	3.48194	33.64979	0.00288	2.90534	28.07852	0.00133
FF3FM	3.86189	37.94829	0.00295	3.37938	33.20697	0.00256	2.87057	28.20782	0.001236
FF5FM	3.56686	35.64765	0.00265	3.08307	30.8126	0.00221	2.61566	26.14198	0.00107
FFC4FM	3.51702	34.85517	0.00272	3.08709	30.59447	0.00243	2.55053	25.27807	0.00105
FFC6FM	3.32483	33.51647	0.00250	2.88740	29.10709	0.00216	2.38848	24.0786	0.00094
Panel J: 9 portfolios HML-RMW									
SFM	1.66971	16.13615	0.00368	1.59507	15.41489	0.00339	0.83826	8.10135	0.00159
FF3FM	1.52249	14.96049	0.00352	1.40922	13.84753	0.00313	0.71340	7.01026	0.00150
FF5FM	1.31546	13.1469	0.00322	1.18930	11.8860	0.00278	0.62063	6.20286	0.00124
FFC4FM	1.42436	14.11605	0.00337	1.31143	12.99687	0.00309	0.76124	7.54462	0.00133
FFC6FM	1.27368	12.8395	0.00315	1.15151	11.60803	0.00281	0.68712	6.92699	0.00118
Panel K: 9 portfolios HML-CMA									
SFM	2.38917	23.08903	0.00327	2.58377	24.96977	0.00322	1.11884	10.81296	0.00183
FF3FM	2.38875	23.47265	0.00314	2.45408	24.11469	0.00309	1.19257	11.71889	0.00185
FF5FM	2.27421	22.72874	0.00282	2.27152	22.7019	0.00290	1.24300	12.42303	0.00171
FFC4FM	2.27061	22.50271	0.00307	2.28362	22.63175	0.00320	1.25614	12.4495	0.00189
FFC6FM	2.18805	22.05701	0.00282	2.157	21.74414	0.00303	1.28126	12.91659	0.00177
Panel L: 9 portfolios HML-MOM									
SFM	3.48915	33.71928	0.00361	3.24388	31.34913	0.00333	2.70946	26.1855	0.00178
FF3FM	3.43989	33.80151	0.00350	3.08963	30.35982	0.00312	2.70446	26.57552	0.00176
FF5FM	3.24195	32.40046	0.00323	2.90761	29.05917	0.00280	2.63022	26.28743	0.00162
FFC4FM	3.26374	32.34505	0.00337	2.99343	29.66625	0.00309	2.70759	26.83464	0.00172
FFC6FM	3.13503	31.60320	0.00316	2.87145	28.94630	0.00283	2.65358	26.7510	0.00162
Panel M: 9 portfolios RMW-CMA									
SFM	4.81920	46.57291	0.00253	4.50002	43.48856	0.00225	2.97183	28.72110	0.00113
FF3FM	5.09099	50.0257	0.00240	4.65529	45.74453	0.00201	3.13615	30.81754	0.00109

	TASI benchmark			MSCI benchmark			S&P benchmark		
	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|	F-statistic	J-Statistic	Mean |α|
FF5FM	4.94694	49.44035	0.00209	4.48175	44.7913	0.00171	3.14915	31.47388	0.00110
FFC4FM	4.88483	48.41066	0.00222	4.47320	44.33146	0.00194	3.07386	30.46472	0.00114
FFC6FM	4.77977	48.18324	0.0020	4.33760	43.72612	0.00167	3.06938	30.94285	0.00115
Panel N: 9 portfolios RMW-MOM									
SFM	3.66591	35.42749	0.00289	3.34607	32.33674	0.00261	3.05333	29.50874	0.00122
FF3FM	3.50231	34.414	0.00276	3.16579	31.10819	0.00241	2.89359	28.43406	0.00117
FF5FM	3.22549	32.2360	0.00243	2.90097	28.99275	0.00211	2.68386	26.82357	0.00104
FFC4FM	3.21590	31.8709	0.00255	2.93906	29.12741	0.00227	2.67865	26.54781	0.00097
FFC6FM	3.02424	30.4863	0.00231	2.74932	27.71507	0.00201	2.53235	25.52893	0.00098
Panel O: 9 portfolios CMA-MOM									
SFM	4.97816	48.10916	0.00286	4.86562	47.02172	0.00258	4.37957	42.32612	0.00131
FF3FM	4.61470	45.34559	0.00275	4.50473	44.26509	0.00237	4.07995	40.09185	0.00129
FF5FM	4.34922	42.9364	0.00240	4.23692	42.34447	0.00197	3.86902	38.66846	0.00121
FFC4FM	4.33245	43.46672	0.00253	4.24821	42.10170	0.00225	3.92180	38.8686	0.00123
FFC6FM	4.13139	41.6471	0.00228	4.03923	40.71830	0.00194	3.74363	37.74006	0.00119

Note. The test the efficiency of SFM, F-F-three, F-F-five, F-F-Carhart-four, and F-F-Carhart-six factor models to explain monthly mutual fund excess returns on 9 Market-SMB portfolios (Panel A), 9 Market-HML portfolios (Panel B), 9 Market-RMW portfolios (Panel C), 9 Market-CMA portfolios (Panel D), 9 Market-MOM portfolios (Panel E), 9 SMB-HML portfolios (Panel F), 9 SMB-RMW portfolios (Panel G), 9 SMB-CMA portfolios (Panel H), 9 SMB-MOM portfolios (Panel I), 9 HML-RMW portfolios (Panel J), 9 HML-CMA portfolios (Panel K), 9 HML-MOM portfolios (Panel L), 9 RMW-CMA portfolios (Panel M), 9 RMW-MOM portfolios (Panel N), 9 CMA-MOM portfolios (Panel O). TASI, MSCI, and S&P were employed as the market factor separately for each set of 9 regressions across SFM, F-F-three, F-F-five, F-F-Carhart-four, and F-F-Carhart-six factor models. GRS F-test and J-test statistics test whether the estimated values of 9 portfolios intercepts (alphas) are jointly zero, MAA |α| is the average absolute value of the 9 intercepts (alphas).

Appendix C

Variance inflation factor (VIF) tests for multicollinearity detection corresponding to estimations in Table 5.11

Panel A	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before R	(6) After R
TASI-RP	1.19	1.60	1.17	1.23	1.60	1.28
SMB	1.90	2.39	2.02	1.68	1.76	2.46
HML	1.31	1.50	1.59	1.27	2.10	1.46
RMW	1.67	2.10	1.67	1.64	1.72	2.40
CMA	1.20	1.41	1.27	1.32	1.51	1.20
MOM	1.14	1.19	1.30	1.11	1.20	1.23
VIF Average	1.4	1.7	1.5	1.38	1.65	1.67
Panel B	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before R	(6) After R
MSCI-SADI-RP	1.14	1.66	1.19	1.20	1.70	1.23
SMB	1.87	2.37	2.03	1.74	1.75	2.40
HML	1.31	1.50	1.52	1.22	2.19	1.46
RMW	1.67	2.10	1.67	1.64	1.76	2.41
CMA	1.20	1.49	1.24	1.27	1.55	1.22
MOM	1.14	1.20	1.31	1.07	1.22	1.22
VIF Average	1.39	1.72	1.49	1.36	1.69	1.66
Panel C	(1) Overall	(2) FC	(3) Bullish	(4) Bearish	(5) Before R	(6) After R
S&P-SADITR-RP	1.18	1.59	1.22	1.18	1.60	1.26
SMB	1.89	2.38	2.06	1.63	1.75	2.44
HML	1.32	1.50	1.56	1.25	2.10	1.46
RMW	1.67	2.10	1.70	1.63	1.71	2.40
CMA	1.20	1.40	1.25	1.25	1.53	1.20
MOM	1.15	1.21	1.34	1.08	1.21	1.24
VIF Average	1.4	1.7	1.52	1.34	1.65	1.67