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School of Politics, Economics and International Relations

Examining Investor Behaviour in the Saudi Stock Markets: Insights into Disposition Effect, Herd Mentality and Inclination toward Shariah-Compliant Investments

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Declaration

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Omar Abdulrahman A Alarfaj

September 12, 2025

Abstract

This thesis examines investor behaviour in the Saudi stock markets (SSM), with a focus on various psychological and behavioural aspects such as the disposition effect, herd mentality, and investors' inclination toward Shariah-compliant investments. These three areas collectively examine the psychological and behavioural dimensions underlying market participants' regret aversion and fear of missing out within the context of the SSM including the associated market anomalies and behavioural biases. Following a brief introduction (1), the research findings that contribute to the existing literature are discussed and explored in Chapters 2, 3, and 4.

Chapter 2 concentrates on investigating the presence of the disposition effect in the SSM by analyzing the trading behaviours of large brokerage retail investors and equity mutual fund managers during two distinct periods: the holy month of Ramadan and the COVID-19 pandemic. Utilizing a novel dataset of daily trading records from 2019 to 2021, the study identifies notable differences between investor types. Mutual fund managers consistently demonstrate a preference for realizing losses over gains while brokerage investors exhibit more heterogeneous behaviours, mainly showing no preferences for either stock gains or losses. Additionally, a panel event study reveals that Ramadan fasting does not significantly alter disposition-driven trading, but the COVID-19 pandemic significantly impacts the trading patterns of both investor groups.

Chapter 3 examines herding behaviour in the SSM around the inclusion of its main market (Tadawul) in the global Emerging Market (EM) indices, a major milestone in Saudi capital market reforms under Vision 2030. Using three unique stock market portfolios and applying established herding detection models, the analysis reveals persistent herding behaviour before and after inclusion, particularly among local investors. However, herding behaviour within the set of stocks accessible to Qualified Foreign Investors (but still available to local investors) becomes statistically insignificant following the inclusion, except when the market is experiencing downturns. Further analysis suggests that while intentional herding predominates, spurious herding arises among local investors, especially during declining markets following the SSM's inclusion in EM indices.

Chapter 4 attempts to develop a regret-augmented portfolio optimization framework to quantify the psychological cost of regret faced by Shariah-compliant investors in the SSM. Using daily stock data from 2018 and 2023, the study compares strict and moderate Shariah adherence scenarios by constructing optimal portfolios under both constraints. Based on the 2018 model results, strict Shariah-compliant investors face an opportunity cost of 0.333 to 0.712 Sharpe ratio points while moderate adherents incur a lower cost between 0.324 and 0.404 points. When regret aversion is incorporated into the optimization, the preference-regret model delivers the best trade-off between Shariah compliance, portfolio performance and risk management. The findings highlight that regret aversion significantly shapes asset allocation decisions and that behavioural models better capture investor preferences than the classical Markowitz framework. The findings are further validated using 2023 data, which confirm similar trends to 2018, though the impact of regret aversion is less significant due to more favourable market conditions seen during the year 2023.

Keywords: Behavioural Bias, Prospect Theory, Regret Aversion Theory, Herd Behaviour, Behavioural Finance, Financial Econometrics, Financial Markets Modeling.

JEL Classification Code: C5, C58, D91, G10, G11, G14, G17, G40, G41

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"In the name of Allah (the God Almighty), the Most Gracious, the Most Merciful" All Praise be to Him (the God Almighty), the Lord and Sustainer of the Worlds; and may His blessings and peace be upon our Prophet Muhammad, his brothers among the previous Prophets and Messengers, and upon all his righteous relatives and companions.

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List of Abbreviations

COVID-19	Coronavirus Disease 2019
SSM	Saudi Stock Markets
CMA	Capital Market Authority
CAPM	Capital Asset Pricing Model
TASI	SSM Tadawul's General Index
PGR	Proportion Gain Realized
PLR	Proportion Loss Realized
DISP	Disposition Spread
DISP-RATIO	Disposition Ratio
QFI	Qualified Foreign Investor
EM	Emerging Markets
CSSD	Cross-sectional Standard Deviation of Returns
CSAD	Cross-sectional Absolute Deviation of Returns
S1U1	Investment Scenario 1 and Shariah-compliant Universe (U1)
S1U2	Investment Scenario 1 and Non-Shariah-compliant Universe (U2)
S2U1	Investment Scenario 2 and Shariah-compliant Universe (U1)
S2U2	Investment Scenario 2 and Non-Shariah-compliant Universe (U2)
S1AOU	Regret Computed for Investment Scenario 1 Against Shariah-compliant Universe (U1)
S2AOU	Regret Computed for Investment Scenario 2 Against Shariah-compliant Universe (U1)

S1AU2	Regret Computed for Investment Scenario 1 Against Non-Shariah-compliant Universe (U2)
S2AU2	Regret Computed for Investment Scenario 2 Against Non-Shariah-compliant Universe (U2)

Chapter 1

Introduction

The early twenty-first century has witnessed significant transformations in global economic and financial systems. This era was characterized by a series of disruptive events and significant developments including the collapse of the dot-com bubble and the substantial consequences of the high-risk home mortgage crisis in 2008. Furthermore, the complexities and challenges surrounding the European sovereign debt crisis, the COVID-19 pandemic, and the most recent US-Chinese trade conflicts have substantially challenged the modern established financial practical frameworks. These events and developments have substantially reshaped the underlying dynamics of global financial markets and influenced the transformation of the investment decision-making process reflecting a new era of complexity in the global financial system. Moreover, those periods of market volatility are typically associated with market overreaction, which contradicts the prevailing assumptions of efficient market theory and investor rationality. In fact, a variety of research papers and theories, particularly within the behavioural economics and finance domain, have attempted to interpret this phenomenon of market overreaction premising that investors exhibit irrational inclinations and their decision-making process is influenced by emotional factors rather than purely fundamental considerations.

From a historical perspective, the analysis of financial markets has primarily relied on classical theoretical frameworks derived from the classical utility theory and efficient markets hypothesis, which, despite their methodological elegance, have often struggled to anticipate or comprehensively explain the prevalence of market anomalies and unconventional investor behaviours. Consequently, behavioural financial theories have become essential in offering a refined understanding that bridges the gap between psychological influences and financial economic principles; thereby, enriching our comprehension of investor behaviour and irregular market patterns. They have established that, in addition to rationality, investors' financial and investment decisions are influenced by psychological and demographic[1] factors, making their choices less than fully rational. As a result, financial and investment decisions are no longer viewed solely as rational reactions to market data and information; rather, the human factors of emotion and cognitive perception have emerged as central considerations. This vital shift enhances the financial economics literature and enables valuable cross-disciplinary discourse within the fields of social science.

This thesis consists of three academic essays that examine and investigate investor behaviour in the context of Saudi stock markets (SSM), with a focus on various psychological and behavioural aspects including the disposition effect, herd mentality and investors' inclination toward Shariah-compliant investments. These academic works share a common thread in their empirical examination of market participants' regret aversion and fear of missing out in the SSM, along with the associated psychological and behavioural dimensions including market anomalies and behavioural biases. More precisely, the paper in Chapter 2 undertakes an empirical examination of the disposition effect during the Ramadan season and the COVID-19 pandemic, while also providing a comparative analysis between large retail investors and institutional investors. Additionally, Chapter 3's paper investigates the presence of herding behaviour in foreign and domestic investments whereas Chapter 4 has a paper focuses on examining and quantifying the psychological implications of investors concentrating their investment portfolios solely in Shariah-compliant stocks utilizing the Markowitz regret framework in the portfolio optimization process. Although the Saudi economy and its stock markets are substantial on a global scale, academic literature has yet to devote sufficient attention to the investment decision-making process in the SSM. Furthermore, the recent inclusion of the SSM in the leading emerging market (EM) indices such as MSCI and FTSE Russell emphasizes the importance of examining investors' trading patterns and the behavioural aspects that shape the investment decision-making process within this market. Therefore, this comprehensive thesis is motivated to address the gaps in the literature by conducting in-depth empirical examinations of diverse behavioural biases including the disposition effect, herd mentality and regret aversion as exhibited by distinct investor types in the SSM during varying events and time horizons.

These three academic studies collectively make a significant contribution to the growing body of academic literature surrounding investor behaviour. Through robust empirical analyses, they offer insights into the unique trading patterns and psychological factors in-

[1] Individual attributes, such as age, gender, income, education, cultural background and geographic location, can significantly influence how people perceive risk, process financial information and make investment decisions.

fluencing various investor cohorts and groups within the SSM (e.g. Retail and Institutional investors in Chapter 2, Foreign and Domestic Investors in Chapter 3, and Strict and Moderate Shariah-complaint Investors in Chapter 4), particularly during specific events and periods (e.g. Ramadan Season and COVID-19 pandemic in Chapter 2, and Before and After the SSM inclusion in the EM indices in Chapter 3). The application of diverse statistical, mathematical and econometric methodologies, as discussed in depth within these three academic works, enhances the academic and expert understanding of the complexities inherent to investment decision-making processes in this substantial financial economics discipline. Thus, this research project comprehensively addresses several gaps in the existing academic literature by empirically investigating investor behaviour across diverse events and investor cohorts within the SSM employing various statistical, mathematical and econometric analytical tools.

The empirical analysis in Chapter 2 examines the presence of the disposition effect in the SSM and investigates the behavioural trading patterns of two investor types (Large brokerage retail investors and equity mutual fund managers) during the holy month of Ramadan and the COVID-19 pandemic. The rationale for examining these two time periods is that during Ramadan, many investors, predominantly Muslim, will be trading while fasting, which presents an interesting opportunity to analyze and identify any impact of this religious practice on the disposition effect trading behaviour. Additionally, the study in Chapter 2 aims to explore whether there are any shifts in this trading behaviour during the period of intensified uncertainty brought about by the recent COVID-19 crisis. Therefore, this research is specifically motivated to provide a detailed comparative investigation of the trading behaviour of two investor categories, focusing on the distinct time periods of Ramadan and the COVID-19 pandemic.

This Chapter bases its empirical analysis on a novel dataset obtained from the data management office of the Capital Market Authority (CMA), the financial markets regulator in Saudi Arabia. This dataset comprises the daily trading records of the 20 most actively trading brokerage accounts and the 20 most actively managed local equity mutual funds in the SSM over three years from January 1st, 2019, to December 31st, 2021.

The empirical work in Chapter 2 is divided into two stages. The first stage involves identifying the prevalence of the disposition effect in the daily trades of brokerage accounts and mutual funds using a statistical approach, and examining the impact of stock gains and losses on the stock proportion realized through a fixed-effect panel data regression model. To robustly assess the presence of the disposition effect in the SSM, the statistical approach developed by Odean (98 A) is applied across various levels of analysis (Trade transactional level for each segment and individual account/fund level). Furthermore, the unobserved heterogeneity between the two investor groups is analyzed to determine whether their presence biases the findings from this investigation stage. The findings from both levels of examination are almost consistent, indicating that, on average, brokerage investors do not exhibit clear positive or negative disposition effects while mutual fund managers demonstrate a strong preference for realizing losses over gains. However, the heterogeneity assessment suggests that brokerage investors are more diverse in their trading behaviours compared to top equity mutual fund managers, who tend to share more common characteristics such as being managed by professional teams with a high level of experience and qualifications. The empirical part of how the magnitude of gains and losses impacts the proportion of gains and losses realized indicates that brokerage investors in the sample tend to frequently realize the majority of their stock positions on a daily basis, regardless of whether they have incurred gains or losses. Once stock gains or losses are observable, brokerage investors respond differently by placing more weight on avoiding realizing stock losses though the relationship is only statistically significant with the stock gains. In contrast, both stock gains and losses appear to positively influence the proportion of returns realized by mutual fund managers.

This chapter's second stage of analysis examines the trading patterns associated with the disposition effect before and after specific events, such as the holy month of Ramadan and the COVID-19 pandemic. Utilizing a panel event study approach, this investigation aims to uncover the impact of those two events on the disposition-driven trading behaviours of retail and professional investors within the SSM. The regression analysis findings indicate that the holy month of Ramadan did not have a statistically significant effect on the disposition trading behaviour of the two investor types examined. In contrast, the event study approach and difference in means t-test reveal that the COVID-19 pandemic had a statistically significant impact on the disposition trading patterns of both mutual fund managers and brokerage account investors.

Following the empirical examination of a well-known market anomaly (Disposition effect), considered to be associated with investors' regret aversion and fear of missing out, in Chapter 2, the academic work presented in Chapter 3 expands the investigation by examining another prevalent behavioural bias, herding behaviour, which is understood to be influenced by the concepts of regret aversion and the fear of missing out. More specifically, it investigates the impact of the redistribution of stock trading activity, driven by the inclusion of the SSM's main market (Tadawul) in the global EM indices, on the herding behaviour in the SSM. As part of the capital market reforms under the Saudi Vision 2030, Saudi Arabia established the

Qualified Foreign Investor (QFI) program in June 2015 to facilitate direct market access for international investors. In March and June 2018, the CMA announced that Tadawul would join the FTSE Russell Secondary EM and MSCI EM indices. Alongside this announcement, the plan for the anticipated inclusion was communicated to take place over the following year of 2019. Hence, the investigation in Chapter 3 is motivated by the recognition of significant herding tendencies in the SSM, as identified by various prior academic studies. It seeks to evaluate the policy of Tadawul's inclusion in the EM indices and assess its potential impact on the observed herding behaviour in the SSM.

The research discussed in Chapter 3 proceeds with the investigation by constructing three investment portfolios using the market data of the stocks listed on the SSM prior to 2019. These portfolios were designed to evaluate the impact of Tadawul's inclusion in the global EM indices on the observed herding behaviour within the SSM. The first portfolio includes all 193 listed companies before 2019. The second portfolio focuses on the 86 stocks available to QFIs while the third concentrates on the remaining stocks exclusively accessible to local investors. Furthermore, the estimations are conducted across three time periods including the overall study period from 01/09/2014 to 25/01/2024, the sub-period before Tadawul's inclusion (01/09/2014 to 31/12/2018), and the sub-period after the inclusion (01/01/2019 to 25/01/2024).

The Chapter 3's empirical work is organized into two components. The first part explores the presence of herding behaviour across all the constructed portfolios and throughout the specified time periods using the method proposed by Christie and Huang (1995) and further developed by Chang et al. (2000) while the second part delves into analyzing the characteristics of the herding behaviour observed within the investment portfolios during the designated time frames following Galariotis et al. (2015)'s empirical approach. The regression analysis applied in the first part indicates persistent herding behaviour within the SSM, observed both before and after the market's inclusion in the global EM indices. This herding tendency is particularly well-defined among local investors although the intensity varies across different market conditions and investment portfolios. Interestingly, for the stocks associated with QFI's investments, the herding behaviour becomes statistically insignificant during the period following the inclusion except when the market is experiencing a declining trend. In terms of herding behaviour nature, the regression analysis suggests that the observed herding behaviour in the SSM can primarily be characterized as intentional herding rather than spurious herding conduct. Nevertheless, local investors have been observed to engage in a form of spurious herding behaviour under various market conditions, particularly during periods of market decline during the period following the inclusion in the EM indices. In fact, the study findings suggest that the intentional herding behaviour becomes statistically insignificant among the stocks associated with QFI investments following the inclusion in the EM indices. However, the intentional herding conduct remains statistically significant for the stocks involving only local investment trades during this period.

As the last part of this thesis, the empirical research provided in Chapter 4 quantitatively evaluates the psychological cost of regret associated with a focus on Shariah-compliant investments using the Markowitz regret optimization model and daily stock market data from two time periods: 2018 and 2023. This approach is adopted because the classical Markowitz optimization model has certain limitations, as it neglects higher-order return characteristics like return skewness and kurtosis, which can be crucial for investors exhibiting loss aversion or regret aversion. Consequently, these types of investors may not be fully satisfied with the outcomes provided by the classical model. Recent advancements in the field have integrated the psychological factor of regret aversion into the mean-variance portfolio optimization framework, validating its effectiveness in addressing and resolving the identified limitations. Building upon these advancements, this Chapter 4 study develops a practical mathematical framework, inspired by the previous empirical model introduced by Baule et al. (2019), to help Shariah-compliant investors align their investment strategies with their religious principles. The key objective of this study is to underscore the essential role of psychological factors, such as regret aversion, in influencing investment decision-making within the underexamined domain of Islamic financial markets.

Using the mathematical framework proposed in Chapter 4, this academic work seeks to assess the potential regrets that may arise for investors from both their investment options that are Shariah-compliant and the non-overlapping, non-Shariah-compliant investment universe that is inaccessible to them. In fact, the proposed framework assumes the existence of two distinct, non-overlapping investment universes within the overall SSM market universe: an investable universe and an uninvestable universe. Moreover, the research presented in this chapter explores two distinct investment scenarios (Strict and Moderate Shariah Adherent) stemming from the varying Shariah-compliant classifications. It analyzes the influence of regret aversion on the optimization of risk-adjusted return portfolios and their asset allocation. In the first investment scenario, investors have access to a limited set of Shariah-compliant stocks and are required to construct optimal portfolios within this constrained investment universe (Including only Pure classification). Conversely, the second scenario provides investors with greater flexibility, allowing them to select from a larger pool of Shariah-compliant stocks that span two distinct classifications (Including both Pure and Mixed stocks).

Based on the optimization process findings of 2018 analyzed in Chapter 4, the empirical evidence suggests that strict Shariah-compliant investors face a Sharpe ratio opportunity cost between 0.333 and 0.712 points, while moderate Shariah-compliant investors experience a comparatively lower cost, ranging from 0.324 to 0.404 points. When regret aversion is incorporated into the portfolio optimization process, this research paper's results conclude that the preference-regret model (where both the regret and traditional risks are controlled), incorporating average regret aversion, provides the optimal balance between Shariah compliance, portfolio performance, and risk management across the two investment scenarios examined. The analysis conducted in this chapter reveals that while return-regret models (which account only for the regret risks) may appeal to investors seeking high absolute expected returns, they also subject portfolios to increased risk and volatility. The findings also demonstrate that as the scope of non-Shariah-compliant investment opportunities becomes more restricted, the likelihood of experiencing regret diminishes accordingly. Therefore, the study emphasizes the vital importance of a well-defined delineation of the investor's investment universe within the regret model framework. This is essential to precisely evaluate the potential for regret and determine the optimal portfolio allocations that align with the investor's requirements.

Next, this study further strengthens its empirical analysis by conducting a comparative examination of the optimal allocation process at the individual stock level. The findings indicate that utilizing different portfolio optimization models leads to significantly divergent asset allocations, particularly when considering behavioural preferences and Shariah-compliance constraints. While the classical Markowitz model emphasizes diversification and mean-variance optimization, regret-augmented models better reflect the psychological tendencies of investors, including their reluctance to incur opportunity costs when adhering to Shariah-compliant investment principles. To test the robustness of the results, the study re-runs the optimization using 2023 data, showing similar trends to 2018 though the regret effect is weaker due to improved financial conditions observed during the latter year.

The final chapter of this thesis, Chapter 5, summarizes the key findings and contributions of the research project, and identifies potential questions and areas for future research and investigations.

Chapter 2

Disposition Effect Empirical Investigation in the Saudi Stock Markets During Ramadan Season and COVID-19 Pandemic: A Comparison Between Large Retail and Institutional Investors

2.1 Introduction

> "If one looks at data over long intervals of time, it appears that the stock market is anything but efficient... It should be clear that human patterns of-less-than-perfectly rational behaviour are central to financial market behaviour, even among investment professionals."
>
> *Robert Shiller*

2.1.1 Background

Financial markets are playing a significant role in the modern economies and result subject to a vast amount of empirical and theoretical research. Research of financial economic theories have thus been developing over the several past few decades with attempts to comprehend investors' rationality in the financial markets through the utilization of new models (Alquraan et al., 2016). The classical financial theories presumed that whenever investors are taking stocks investment decisions, they do not have difficulties since they are well-informed, cautious, and consistent. In fact, capital asset pricing model (CAPM) and modern portfolio theory (MPT) assume that investors are not confused concerning the limit of information that is availed to them and moreover not guided by their behavioural factors (Ali et al., 2013).

However, most recent and well-structured studies in the developed capital markets have established that several phenomena (Known as market anomalies) pertaining to stock investment decisions cannot be justified and explained by those traditional financial theories (Areiqat et al., 2019). In reality, those who invest in capital markets generally take many diverse and significant decisions; the most usual ones are taking investment determinations to optimize their fortunes relaying on some fundamental techniques to evaluate the expected price of a security, while others consider understanding technical techniques of market timing to optimize their wealth, which implies that the investment decision making process is not perfectly based on the investors' rationality.

One of the most common market anomalies observed in financial markets and stock markets, in specific, is the disposition effect. As per Statman et al. (2006) definition, the disposition effect reflects investors' willingness to realize profits and gains too soon by selling shares or stocks appreciated in value while deferring and postponing the realization of their losses for too long. This phenomenon is a form of irrational behaviour explained by Kahneman and Tversky (1979) in the loss aversion principle, an important concept associated with their prospect theory. In this theory, investors are prone to value gains and losses differently by focusing more on perceived gains against perceived losses. Two of the pioneering researchers who initially investigated and confirmed the existence of this market anomaly in financial markets and called it "the disposition effect" are Shefrin and Statman (1985). According to their findings, investors despise the anguish of regret that comes with a loss. As a result, people tend to postpone acknowledging their losses while recording their earnings on a regular basis, as explained before, a phenomenon known as the disposition effect. Moreover, the researchers highlight that having the investors disclose their mistakes to others might intensify this remorse while making a profit adds to their pride.

After Shefrin and Statman (1985) presented the disposition effect theory, several empirical evidence in the existence of this trading behaviour in developed financial markets has been introduced and confirmed by a couple of financial economists such as Odean (98 A, 1999) and Barber and Odean (2000, 2001, 2002). Additionally, Weber and Camerer (1998) conducted an experimental study and were able to confirm and document the disposition effect for investors.

Consequently, it is essential to investigate financial market anomalies and try to address the behavioural aspects of investors that influence the stock investment decisions. In this paper, we aim to examine the presence of the disposition effect in the Saudi Stock Market (SSM) by analyzing the trading behaviour of a specific subset of investors: the Top 20 most active retail brokerage accounts and equity mutual fund managers, representing large retail and institutional segments, respectively. While this sample does not encompass the full spectrum of retail investors in Saudi Arabia, it offers insights into the behaviour of the most active participants in the market. Additionally, this paper will make an attempt to study and investigate any changes in the disposition trading behaviour during the holy month of Ramadan and the COVID-19 pandemic by conducting an event study. The rationale behind looking at these two time periods is that during Ramadan, many investors, mostly Muslim, will be trading while fasting, which makes it interesting to analyze and identify any impact coming from exercising the worship of fasting on the disposition trading behaviour during this month. In the case of looking at COVID-19 period, this paper is also ambitious to look if there are any shifts in this trading behaviour during the time of a crisis by taking the most recent crisis as an example.

2.1.2 Research Objective, Motivations and Contributions

The key aim of this research is to examine the existence of the disposition effect in the SSM and explore the behavioural trading patterns of two types of investors (Large Brokerage retail investors and equity mutual fund managers) during the holy month of Ramadan and COVID-19 pandemic and compare their findings with the findings from the trading records in normal days. This research paper will contribute to the existing literature in different aspects. First, analyzing investors' behaviour and its impact on stock investment decisions in the SSM has not yet received a sufficient amount of attention in the literature even with the size of the Saudi economy and its stock markets as one of the biggest across the globe, especially, after listing one of the most valuable listed companies "Saudi Aramco" with a market cap of around 1.66 trillion US dollars (as of April 23rd, 2025). Second, the recent inclusion of the SSM in emerging market indices such as MSCI and FTSE Russell increases the importance of evaluating the investors' trading patterns and the behavioural aspects impacting the investment decision making process in the SSM. Third, this study, in particular, is motivated to provide a close-up investigation of two types of investors' trading behaviour in a comparison manner concentrating on a specific time periods such as Ramadan and COVID-19 pandemic. To sum up, this research comes to investigate the disposition effect in the SSM and seeks to tackle the behavioural bias of investors, which impact the stock investment decision making process. Alkhaldi (2015) have investigated the 2006 SSM market crash, and established that the crash was due to factors like poor investor's experience and knowledge. Inadequacy of experience and knowledge may guide investors to a cognitive bias while making their investment decisions. Thus, the understanding of investors' behaviour in the stock market is critical as it may assist in discovering and addressing the challenges that may exist in the market.

2.2 Literature Review

In this section, the paper emphasizes on the development of the objective through the literature by explaining some of the popular psychological biases associated with the disposition effect, and how they have been given acceptance by financial economists in pushing anomalies in stock returns. After that, this section will provide a brief literature review on the disposition effect investigation followed by a summary of some facts about the SSM, and a brief review of the behavioural finance literature conducted in this stock market.

2.2.1 Behavioural Biases and the Disposition Effect

The behavioural theory posits that people are not almost as rational as has been established by traditional finance theory. According to Sewell (2007), behavioural finance provides explanations and descriptions to investors that are peculiar on how biases and emotions move share prices. The concept that psychology is the driver of the stock market is a common idea that has been established by theories that propose the idea that markets are not efficient (Kahneman and Tversky, 1979; De Bondt and Thaler, 1985; Shiller, 2003; Slezak, 2003; Hirshleifer et al., 2013).

Advocates of the efficient market hypothesis (EMH) claim that any new information that has relevance to the value of a company is rapidly priced by the market (Modigliani and Miller, 1958; Sharpe, 1964; Fama, 1970). As a counter to the EMH, Kahneman and Tversky

(1979) developed their theory "Prospect theory", which assumes that market agents are not perfectly rational, and that asset prices are influenced by human behaviour. They suggest that people place different values on wins and losses and base decisions more on the prospect of profits than on the potential of losses. Generally, the behavioural theory argues that some of the financial market anomalies can be better understood under the assumption that some agents are not completely rational. The disposition effect is a form of market anomalies resulting from many cognitive errors or biases analyzed and discussed in the behavioural finance studies. Below are some of these behavioural cognitive errors and biases that are used in the literature to provide some explanations of the disposition effect presence in the capital markets.

Prospect Theory

Several behavioural economics scholars such as Odean (98 A), Grinblatt and Han (2005), Lucchesi et al. (2015), and Jiao (2017) argue that the prospect theory, which is proposed and developed by Kahneman and Tversky (1979), provides a viable explanation of what leads to the disposition effect. According to this firmly established theory, people seek to avoid risk in winning circumstances such that their utility function is concave. On the other hand, in losing circumstances, they tend to be more open to take risky chances such that their utility function is convex.

This suggests that while investors are reluctant to sell their losing positions, they are more likely to sell their winning positions when the first opportunity arrives. Correspondingly, a loss of any size causes a higher sense of loss than a gain of the same size. For this specific reason, the utility function or the value function, as was called by Kahneman and Tversky (1979) in their prospect theory, in the losing situations seems to be steeper with a convex shape as can be clearly seen in Figure 2.1. Hence, the value function is determined over changes in gains and losses relative to some reference point, usually the purchased price, rather than wealth levels as suggested in the expected utility theory, and that the curve in losing conditions is steeper compared with the curve in winning conditions.

Mental Accounting Bias

According to the claims made by Tversky and Kahneman (1985), Thaler (1985), and Kahneman and Lovallo (1993), Investors will divide all of their investment outcomes into various little portions or several mental accountings. The mental accounting of paper profits and losses, as per Thaler (1999)'s argument, is a bit complex. However, it is intuitively obvious

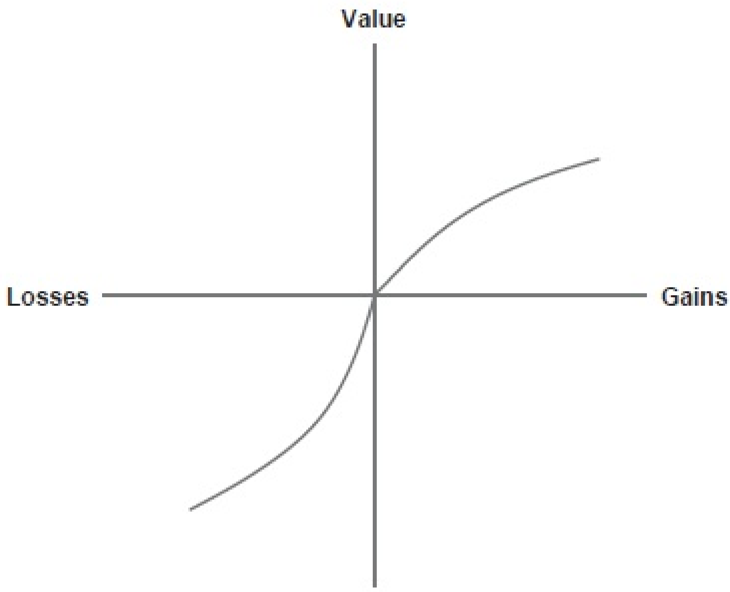


Figure 2.1: Kahneman and Tversky's (1979) Prospect Theory Value Function

that a loss realization hurts more than a paper loss. Since closing an account at a loss is very painful, mental accounting predicts that individuals would be hesitant and reluctant to sell their positions that have decreased in value.

For further demonstrations, the mental accounting shows that investors split their investment prospects into various accounts and bet with their results, completely excluding any possibility of interaction between them. Each of those mental account is worth something different for the investors, so that if the investors realize the losses on any of these mental accounts, then they have to admit and close that account at a loss. Therefore, under the assumption that investors are not entirely rational, it would be difficult for them to sell and ultimately close any of the mental accounts at a loss, which, as a result of this behaviour, might lead to the disposition effect presence in the financial markets (Zahera and Bansal, 2019).

In fact, prospect theory and mental accounting served as the driving forces behind Grinblatt and Han (2005)'s study, which came to measure the cross-section of stock returns to explain momentum in stock prices. Likewise, Shefrin and Statman (2000) developed their investment behavioural portfolio theory inspired by the prospect theory and mental accounting structure as well as Lopes (1987)'s SP/A (Security-Potential/Aspiration) theory. To derive the portfolio theory, they use single account and multiple accounts. Investors with a single account propensity will deposit the entire portfolio into the same account whereas investors with multiple accounts often split their portfolio across those accounts while ignoring the covariance between them. In their empirical investigations, Hsiao and Pi-Chuan (2006) proposed and confirmed that mental accounting is positively associated with the disposition effect.

Regret Aversion and Pride Seeking Biases

Shefrin and Statman (1985) posit that regret is an emotional feeling that is considered as one of the factors contributing to the disposition effect. More precisely, this emotional sense an investor feels related to the ex-post perception that an alternative former decision would have performed better than the one made, which might lead investors to resist the realization of a loss since it serves as evidence that their first judgment was incorrect. Investors, according to Barber and Odean (1999), desire to eliminate feeling regret. In the case of selling gains too soon, investors who hold paper gain stocks are concerned that the stock price may decline and consequently decide to sell the stocks in order to capture and realize those gains. On the other hand, investors who ride paper loss stocks do so because they believe that the price of the stock will increase in the future, and they might be able to minimize those losses if they decide to keep the stocks longer. In support, Shiller (2000) argues that the regret theory can presumably serve in explaining why investors delay selling equities whose value has depreciated and expedite selling those whose value has appreciated.

While liquidating a specific stock at a loss generates regrets, doing it at a gain promotes pride, which means pride is the satisfied alternative to regret. Shefrin and Statman (1985) demonstrate that there is always some level of invisible pride hidden in the investors' minds when they attempt to gain from their investments. This occurs due to the increase in the investors' pride is closely related to the return on investment. Even worse, when successful investments are sold and continue to perform well, this pride suffers causing the investors regret selling their positions. Therefore, regret aversion and pride seeking biases are strongly connected and considered one of the main drivers of the disposition effect in the stock markets. In fact, Hsiao and Pi-Chuan (2006)'s investigation findings indicate that regret aversion is one of the psychological factors which has a significant influence on the disposition effect.

Overconfidence Bias

The disposition effect and overconfidence bias are two cases of cognitive errors that influence investor decision-making process. Along with other behavioural biases, these two significantly affect investors' stock valuation and trading abilities. According to a series of empirical studies conducted in the academic literature, there is a strong correlation between trading activity and previous stock market returns, and both of investors' overconfidence and disposition effect are found to be highly associated with this relationship (Statman et al., 2006; Trejos et al., 2019; Liu and Kan, 2021). However, Statman et al. (2006) argue that overconfidence leads investors to trade asymmetrically between gains and losses, which is a driving force behind the disposition effect. In support, Hsiao and Pi-Chuan (2006)'s investigation results authenticate Statman et al. (2006)'s argument indicating that overconfidence positively influences the disposition effect in the financial markets. These two cognitive errors are forms of heuristics that result from the brain's propensity to use shorter, more intuitive processing steps rather than longer, more extensive ones. Two things set overconfidence apart from the disposition effect. First, the disposition effect is a term used to describe how an investor feels about a particular stock inside their portfolio while overconfidence has an impact on the investment portfolio and the stock markets as a whole (Odean, 98 B; Zaiane, 2013). Second, the disposition effect can only accounts for one side of a trade's motive whereas overconfidence might justify both sides to a particular transaction (Zaiane, 2013).

Self-control Bias

To have self-control is to have emotional control. High self-control investors won't be reluctant to acknowledge gains or losses. In fact, they will even accept a loss if it means preventing bigger losses in the future. In regards with preventing extreme losses, Kleinfield (1993) proposes an unbreakable rule that requires the realization of a loss by predetermining an acceptable certain point; so that once the decline hits that specific point, for example, 10 percent of the initial purchase price, the investor should sell the losers and realize the 10 percent loss of his/her initial investments. According to the findings of Grinblatt and Keloharju (2001) and Odean (98 A), investors do sell more losers toward the end of the year. The tax-loss selling hypothesis is one theory that could be used to explain the situation. It is a result of the US tax code and the December 31st tax year end. Capital losses are deductible under the US tax code and law. As a result, any losses realized before December 31st will be accounted as an offset for the gains realized during the year, and the investor will benefit from that by paying less tax compared with the case if he/she did not realize any losses. The action of selling in December demonstrates the value of self-control. From that, we can conclude that self-control investors are less likely to exhibit the disposition effect since they are less likely to be reluctant to realize their losses. Hsiao and Pi-Chuan (2006) investigation findings are in line with this view suggesting that investors might need to consider practicing several mechanisms (e.g., Kleinfield (1993)'s unbreakable rule) to control their irrational behaviours.

2.2.2 Previous Empirical Studies Investigating the Disposition Effect

The disposition effect is considered as one of the most prominent financial market anomalies that has been empirically investigated in the literature and found to be highly associated with investors' irrational behaviour. Numerous well-known financial economists, including Shefrin and Statman (1985); Odean (98 A); Barber and Odean (1999); Weber and Camerer (1998); Kaustia (2004); and Barberis and Xiong (2009), have acknowledged the disposition effect's prominence, confirmed its presence in the financial markets and pointed out that investors, especially individual and inexperienced, are easily prone to it.

In a unique empirical setting, Odean (98 A) investigates the stock trading records of 10 thousand brokerage accounts obtained from a local discount brokerage house in the United States. The investigation covers a six-year period from 1987 to 1993. He makes a comparison between the proportion of gains realized (PGR) to the proportion of losses realized (PLR) and finds statistical evidence which indicates individual investors are prone to realize a lower proportion of losses than that of gains. In order to determine whether this is the result of portfolio rebalancing, which is a rational action an investor might take to manage their risks, Odean controls for that by examining if sales were for partial holdings of a stock rather than the complete holdings so that partial sales demonstrate a rebalancing approach. The findings are still consistent with the disposition effect theory even after excluding such partial stock sales from the computations. Then, he estimates the costs associated with US investors' disposition effect. He comes to the conclusion that selling a winner rather than a loser will result in a 4.4 percent lower return over the course of a year, indicating that those investors who sell winning stocks and maintain losing ones thinking the latter will ultimately outperform the former are typically making a mistake. Finally, Odean verifies the December effect which is the only month where a slightly larger proportion of losses than gains are realized since investors attempt to lower their tax incidence.

Various subsequent research on the disposition effect across the globe have used and been inspired by these empirical findings of Odean's. For example, in a similar setting, Leal et al. (2006) analyze 1496 Portuguese individual investors' trading activities to examine whether they have a propensity to keep onto their losers and sell their winners. Their empirical findings indicate that all the investors exhibit the disposition effect in their trading and its presence is in every month of the year, even at the end if the fiscal year, which suggests that the December effect appears to have little bearing on investors' preferences. Additionally, Leal et al. (2006) pointed out that more experienced investors are less sensitive to the disposition effect and that the disposition effect is stronger in bull markets.

Similarly, Feng and Seasholes (2005) conducted a study using data from a national brokerage house in China comparable to those used by Odean, demonstrating that the disposition effect was present among Chinese investors as well. This finding in the Chinese stock market was supported by Chen et al. (2007). Furthermore, the disposition effect was evident from 1995 to 1999 in the Taiwanese stock exchange according to research provided by Barber et al. (2007). Their database contains the list of all traders (about 4 million) and all trades (more than one billion). They discovered that Taiwanese investors were twice as likely to sell an appreciated investment than a declining one, and 84 percent of those investors sell winnings more quickly than losers.

In an alternative setting, Weber and Camerer (1998) examine the disposition effect using a controlled experimental framework. Conducting a series of experiments with approximately 100 students from the University of Kiel and Aachen University, they tracked participants' trading behaviour over 14 trading sessions to test two hypotheses: first, whether the disposition effect emerges when reference points are based on the purchase price; and second, whether compelling subjects to liquidate at the end of each period mitigates the effect. In the first setting, subjects displayed a sizable disposition effect, consistent with prospect theory's prediction of risk aversion in gains and risk seeking in losses. In the second, forced liquidation largely eliminated the behavioural bias. A key feature of their laboratory design is the clear and salient definition of the purchase price, which ensures that observed behaviour reflects genuine preference-based tendencies rather than confusion over reference points. In contrast, Birru (2015) exploits stock splits as a natural experiment to show that in real-world markets, investors frequently fail to update their reference prices after nominal changes in share price, leading to a breakdown of the disposition effect. This post-split environment allows Birru (2015) to test the link between the disposition effect and return anomalies, finding that while the breakdown is associated with abnormal price jumps at the split ex-date—consistent with the disposition effect impeding news incorporation—momentum remains robust, implying that the disposition effect is not its sole driver. Together, these two studies highlight how the clarity or ambiguity of reference points critically shapes the measurement and interpretation of the disposition effect, with controlled experiments like Weber and Camerer (1998)'s capturing the bias under idealized conditions, and field evidence such as Birru (2015)'s revealing its interaction with market frictions, investor inattention and price anomalies.

Furthermore, recent research emphasizes that this behavioural bias is not uniform and can be influenced by the decision-making context, particularly when decisions are delegated or made on behalf of others. Two recent experimental and empirical studies, Chang et al.

(2016) and Hermann et al. (2019), offer complementary yet distinct perspectives on how delegation and responsibility affect the manifestation of the disposition effect.

Chang et al. (2016) examined how the disposition effect differs between self-managed (non-delegated) and externally managed (delegated) investments. Through both brokerage account data and a controlled experiment, they proposed a cognitive dissonance[1] framework suggesting that investors are hesitant to realize losses on assets they manage themselves, as doing so would necessitate acknowledging poor decisions, thereby incurring costs to their self-image. Delegation modifies this dynamic by providing a psychological "scapegoat" through a fund manager, thus permitting investors to accept losses without self-blame. This mechanism not only mitigates the disposition effect in delegated investments but can reverse it entirely, leading investors to sell losing delegated assets more readily than winning ones. Furthermore, their findings suggest that the degree of delegation is almost directly proportional to the magnitude of the reverse-disposition effect, and that heightened cognitive dissonance or an increased salience of the manager can amplify this reversal.

In contrast, Hermann et al. (2019) explore trading behaviour when individuals make investment decisions on behalf of others in the absence of direct financial incentives. Drawing on an experimental design based on Weber and Camerer (1998), they distinguish between an "Individual" treatment (trading for oneself) and a "Responsibility" treatment (trading for an anonymous matched counterparty). Their results indicate that inexperienced and prosocial decision-makers exhibit higher disposition effects when trading for others, relative to when they trade for themselves. This amplification is attributed to an increased emotional burden and self-control issues arising from social concern for the beneficiary. Unlike Chang et al. (2016) where delegation facilitates blame-shifting and thus mitigates the behavioural bias, Hermann et al. (2019) identify a channel in which responsibility for others, under conditions of low experience and high prosociality, intensifies the bias.

Taken together, this body of literature review demonstrates that while the disposition effect is a widespread and well-documented anomaly across markets, its manifestation is shaped by both cognitive and contextual factors. Evidence from large-scale brokerage datasets confirms its presence among individual investors in diverse geographical and institutional settings whereas experimental studies such as Weber and Camerer (1998) isolate the bias under conditions of clearly defined reference points, reinforcing its compatibility with prospect theory. Field-based natural experiments, such as Birru (2015), reveal that the effect can break down

[1] Cognitive dissonance is the psychological discomfort stemming from inconsistencies between beliefs and reality. In investing, it emerges when an investor's self-perception as a competent decision-maker conflicts with the experience of financial loss.

when nominal price changes reference points, with important implications for price formation and the persistence of return anomalies like momentum. More recent research, including Chang et al. (2016) and Hermann et al. (2019), further illustrates that the disposition effect is not monolithic: it can be mitigated through mechanisms such as blame-shifting under professional delegation, or conversely, amplified by emotional and prosocial pressures when deciding on behalf of others. These findings collectively suggest that the disposition effect arises from multiple, interacting behavioural channels—ranging from self-image maintenance and investor inattention to social responsibility—and that its strength and direction depend critically on the decision environment, the clarity of reference points and the investor's psychological and social context.

2.2.3 Summarized Facts about the SSM

The only stock exchange in the Kingdom of Saudi Arabia is the Saudi Stock Exchange (Tadawul) that is regulated by the Capital Market Authority (CMA). Under this stock exchange (Tadawul), there are two stock markets, the main stock market and the parallel market known as "Nomu Stock Market". Initially, Saudi Arabia joint-stock companies had their kickoffs in the middle 1930s when the Arab Automobile was launched as the Saudi's first joint-stock company. However, Tadawul's existence can be traced back to the 1970s when it informally came to existence. It had shares listed from 158 companies that covered 15 sectors at the end of 2012. Each of these sectors comprises of companies which have a mutual line of operation. The market sale of capital stock of the shares that were issued by the listed companies, as of 2012, was approximately 1,400 billion Saudi riyals (Asiri and Alzeera, 2013; Kalyanaraman, 2014).

There is also the Tadawul All Share Index (TASI), which is the Main Saudi Stock Market composite index, which on August 1, 2004, was about 6,100 (Kalyanaraman, 2014). It recorded a constant rise throughout the year and closed at about 8,200 at the end of the year, this rising trend prevailed, and the index exceeded the 20,000 level in February 2006, and it reached its highest peak in history at 20,634 on February the 25th. However, TASI thereafter began dropping and hit below 10,000 on October 31st, 2006, and lost approximately 65 percent of its value by the end of 2006 (Alsabban and Alarfaj, 2020). Various studies, like Alkhaldi (2015), and Lerner et al. (2017), inquired on the 2006 SSM crash and established that the crash was a result of diverse factors like poor investor's experience and knowledge. This means that the trades and investment decisions taken place before the 2006 market crash were not perfectly rational. Thus, it is very important to investigate and analyze investors' investment decision making process in order to understand their behaviours and comprehend the type of factors causes such behaviours.

2.2.4 Literature Review Related to Saudi Markets

This sub-section reviews the works of literature that are relevant to the research objectives, especially those that have been conducted in the SSM. Alquraan et al. (2016), for instance, distributed 140 questionnaires at random in their study to investigate Saudi individual investors. They found that Saudi investors are inclined to be overconfident while making their investment decisions. This meant that they have the proclivity to exaggerate their abilities, knowledge, and judgments when it comes to investing. The other researchers, Alsedrah and Ahmed (2017), also conducted research to determine the stock portfolios of Saudis' investors in the SSM. According to them, investors in the SSM seemed to engage in speculative behaviours while making investment decisions. Overconfidence bias was especially cited as their prevailing behaviour.

The third literature under this review is about the work of Matoussi and Mostafa (2016). They focused on behavioural biases, which may drive variations to emerging markets, especially during crises. They researched on Saudi market after the sharp drop in oil prices. They established that Saudi investors are overconfident, sensitive to rumors, mimetic, conservative, and over-opportunistic. This affirms the research which was conducted by Alsabban and Alarfaj (2020).

Alsabban and Alarfaj (2020) investigated the lead-lag relationship between market turnover and market returns by using estimation models (VAR models) and impulse response function (IRF) analysis, which are based on Statman et al. (2006)'s empirical approach. The theory behind this is that positive historical market returns affect investors' levels of overconfidence leading them to trade more, which increases the trading volume in the stock markets. Thus, they went ahead and test this theory covering the period from 2007 to 2018 relying on monthly based analysis. Their VAR model's results and IRF analysis's findings reaffirmed that SSM is characterized by overconfidence behaviour. Their outcomes showed that investors tend to overtrade when they get good returns in the previous month.

The next literature under this section was conducted by Elwani (2016), who attempted to understand the information behaviour of investors in the SSM, as well as the effect of the interposing factors on their behaviours by conducting survey-based research and using closed-ended questions through an online questionnaire instrument. He found that the experience factor has a hugely adverse effect on the behaviour of individual investors to seek information. Put differently, Elwani (2016) found that information searching and information acquisition behaviour in Saudi is determined by overconfidence, the acquisition skepticism, formal information access and regret aversion bias.

In addition to the above studies, Gavriilidis et al. (2016) investigated herding behaviour during the holy month of Ramadan across a range of predominantly Muslim stock markets. Using daily data and comparing Ramadan with non-Ramadan periods, they found that herding behaviour tends to intensify during Ramadan in several markets although the effect varies by country and market conditions. They attributed this pattern to increased social interactions, collective sentiment and the distinctive cultural environment associated with the fasting month. While their study does not specifically focus on the SSM, the documented seasonal shift in investor behaviour during Ramadan offers valuable insights for the Saudi context, as similar social and psychological dynamics may influence other behavioural biases including the disposition effect.

2.3 Data Collection and Methodology

2.3.1 Data

Data Sources and Sample Design

This empirical work utilizes a novel data-set obtained from the Data Management Office at the Capital Market Authority (CMA), which is the financial markets regulator in Saudi Arabia. We sought assistance from the CMA with regards to collecting comprehensive data-sets comprised of all daily trading records and the monthly stock positions and holdings for the most actively trading top 100 retail brokerage accounts, which are held by different investors, and top 50 actively managed local equity mutual funds with the largest trading size. However, given the sensitivity of the data, its confidentiality and the challenge of the collection process administrative costs, we were only able to secure the daily trading records of the 20 most actively trading brokerage accounts and the 20 most actively managed local equity mutual funds in the SSM. In terms of the time frame of the study, our investigation is based on the recent three years spanning from January 1st, 2019 to December 31st, 2021.

Essentially, there are two basic requirements for a brokerage investment portfolio or a local equity mutual fund to be considered for inclusion in our sample. First, the investment/trading strategy has to be active. The second is that those investment portfolios and funds must be among the most active investment portfolios/funds in the stock market with the largest trading size given that their investing behaviour has a substantial influence on the stock market. In the study's time frame, the daily trading records of the 20 brokerage accounts in our sample contain around 3.81 million buy transactions with an average value of 2.13 million Saudi riyals for each observation and around 2.13 million sell transactions with an average value of 2.08 million Saudi riyals for each observation. On the other hand, the daily trading records of the 20 local equity mutual funds in our sample consisted of 728 thousand buy transactions with an average value of 3.44 million Saudi riyals for each observation and around 1.08 million sell transactions with an average value of 3.46 million Saudi riyals for each observation (See Table 2.1). The brokerage trading records of the 20 stock investment accounts in our sample have more than 105 thousand daily observations while the mutual fund trading records of the 20 local equity funds in our sample have about 31 thousand daily observations during the time period under the study. If only including traceable trading records [2], the number of daily observations in the brokerage accounts' trading records dropped to about 87.5 thousand observations whereas the number of daily observations in the mutual funds' trading data decreased to around 17.1 thousand observation.

To attain a more comprehensive understanding of the trading patterns in our obtained data set, Table 2.1 shows the summary statistics for the number of buy/sell trades per day and the number of purchased/sold stocks per each trade along with the total buy/sell transactions with their average values for both of the brokerage accounts and the mutual funds. For the brokerage accounts, the average buy trades placed on a trading day is around 68 trades whereas the average sell trades per day is about 39 trades. In contrast, the average buy trades per day for the mutual funds is lower with approximately 52 trades on each trading day while the average sell trades per day is higher with roughly 72 trades per day. In terms of the number of purchased/sold stocks per trade, the average purchased stocks per trade for the brokerage account is around 1,320 stocks per trade whereas the average of the sold stocks is around 2,226 stocks per trade. For mutual funds, the average purchased stocks per trade is almost 4 times the brokerage accounts' average while the average of the sold stock per trade is slightly higher than what is observed in the brokerage accounts. However, both the total buy and sell transactions observed in the brokerage accounts are higher than those observed in the mutual funds.

[2] Due to the lack of access to investors' holding information including stock positions and average purchased prices, all sell trades with no referenced buy price have been excluded from the analysis. Further details with regards to this process will be provided later in the methodology section.

Table 2.1: Descriptive Statistics of Investor Trades

	Brokerage Accounts				Mutual Funds			
	Mean (Median)	Std Dev	Max	Min	Mean (Median)	Std Dev	Max	Min
Buy Trades per Day	68 (26)	132	7,636	1	52 (27)	125	11,410	1
Sell Trades per Day	39 (14)	76	4,615	1	72 (39)	98	2,301	1
Purchased Stocks/ Trade	1,320 (680)	3,959	500,000	-	4,918 (1653)	49,012	3,773,585	-
Sold Stocks/ Trade	2,226 (1233)	5,871	550,000	1	2,467 (981)	11,800	1,136,092	1
Total Buy Transactions	3,806,214				728,078			
Average Value of Buy Transactions	SAR 2,134,092				SAR 3,435,526			
Total Sell Transactions	2,125,773				1,084,881			
Average Value of Sell Transactions	SAR 2,079,615				SAR 3,461,745			
Number of Observations	105,323				30,597			

Notes. This table compiles the data utilized in our empirical investigations. The investor trade records were obtained from the Capital Market Authority (CMA) and include buy and sell daily transaction history in the Saudi Stock Markets for 20 brokerage accounts and 20 local equity mutual funds from January 1st, 2019 to December 31st, 2020. Medians are provided in parentheses with their relative means.

Characteristics of the Study's Sample

To ensure that our sample accurately represents the population of each investor group (Retail and Mutual Funds), we use the monthly stock market ownership and trading activity report issued by the Saudi Stock Exchange (Tadawul) to determine how much of the monthly total buy and sell traded value of shares is included in our sample. Tables A.1 and A.2 provide an overview of the key aspects of the trading records for the retail brokerage accounts and the local equity mutual funds included in our sample and how well they represent their populations in both of the Main and Nomu stock markets while Tables A.3 and A.4 focus on only the traceable trading records in both markets for each investor group that will be examined in our empirical study. The traceable records are those of the sell trades that can be traced back to their buy transactions which were placed previously during the period under the study. Further explanation will be given later in the methodology section.

From Table A.1, the brokerage accounts included in our sample represent on a monthly basis an average of 9.0 percent of the total buy value traded of the retail brokerage investment segment in the Main market and an average of 8.8 percent of the total sell value traded in the Main market while they represent on a monthly average around 3.8 percent of the total buy value traded in the Nomu market and an average of 3.6 percent of the total sell value traded in the Nomu market. On the other hand, for the case of the local equity mutual funds from Table A.2, our sample represents on a monthly basis an average of 48.3 percent of the total buy value traded of all mutual funds in the Main market and an average of 49.1 percent of the total sell value traded in the Main market whereas it represents about a monthly average of 62.9 percent of the total buy value traded and an average of 27.0 percent of the total sell value traded. However, it is worth mentioning that the mutual funds in our sample are more active in the Main market than in the Nomu market given that they placed their buy and sell trading orders in only four months during the whole three years under the study (see

Table A.2).

Looking at Table A.3, we can see that the monthly average representation ratio of the brokerage sample went down after adjusting for the traceable records from 9.0 percent to 5.7 percent of the total buy value traded and from 8.8 percent to 5.5 percent of the total sell value traded of the retail investment group in the main market. In the Nomu market, the monthly average representation ratio of the brokerage sample decreased slightly from 3.8 percent to 3.7 percent and from 3.6 percent to 3.5 percent of the total buy value traded and the total sell value traded, respectively. Concerning the local equity mutual funds, Table A.4 shows a decrease in the monthly average representation ratio after the adjustment of the traceable records from 48.3 percent to 27.2 percent of the total buy value traded and from 49.1 percent to 18.4 percent of the total sell value traded of the mutual fund investment group in the main market. In terms of the Nomu market, despite the fact that Table A.4 demonstrates that the monthly average representation ratio after the adjustment of the traceable records remains constant at 62.9 percent of the total buy value traded in the market, it shows that the representation ratio has increased from 27.0 percent to 55.6 percent in the sell value traded. Please note this increase is due to the fact that we remain with only one month representable from 36 months of the period under the study while, previously, we had about 4 months out of the 36 months in Table A.2.

2.3.2 Methodology

The Study's Hypotheses Formulation and Its Identification Strategy

The empirical analysis in this study begins by testing whether individual investors using large retail brokerage accounts and local equity mutual fund managers in the Saudi Stock Market (SSM) exhibit behaviour consistent with the *disposition effect*—the tendency to sell winning investments too early while holding on to losing positions for too long. This behavioural bias suggests that investors derive utility from the realization of gains and avoid realizing losses, deviating from the optimal portfolio theory and efficient-market hypothesis.

To assess this behaviour, we compare investors' *Proportion of Gains Realized* (PGR_{it}) with their *Proportion of Losses Realized* (PLR_{it}) over time. A higher proportion of gains realized relative to losses ($PGR_{it} > PLR_{it}$) would indicate the presence of the disposition effect.

We therefore test the following hypothesis:

Null Hypothesis 1. $PGR_{it} \leq PLR_{it}$

Hypothesis 1. $PGR_{it} > PLR_{it}$

Where,

- PGR_{it} = the proportion of gains realized for investor i at time t,
- PLR_{it} = the proportion of losses realized for investor i at time t.

Evidence supporting the alternative hypothesis would imply that both Large retail and institutional investors in the SSM are subject to systematic behavioural biases in their trading decisions.

Once the behavioural bias is assessed in the SSM, further investigations and tests will be conducted concentrating on specific time periods such as the time of the holy month of Ramadan, where all Muslim investors will be fasting during the trading hours, and the COVID-19 pandemic, which is considered as a difficult time to be trading in the stock markets. In the month of Ramadan, we expect that the disposition effect to be stronger than the disposition effect in the other months given that all investors are trading while fasting, which might affect their judgements and increase their irrational trading behaviours. On the other hand, in the time of COVID-19 pandemic, we predict the effect to be weaker during COVID-19 pandemic since most investors will be more willing to realize their losses (Cash is king during recessions) and most of the markets are in the bearish stage (meaning very few stocks might be doing well and sold at gains during these difficult times). Thus, the null hypothesis and the alternative hypothesis in the time of Ramadan and COVID-19 pandemic compared with the other times are specified below.

1. Ramadan's null and alternative hypotheses;

   Null Hypothesis 2. $DISP - RATIO_{iRamadan} \leq DISP - RATIO_{iNot'Ramadan}$

   Hypothesis 2. $DISP - RATIO_{iRamadan} > DISP - RATIO_{iNot'Ramadan}$

2. COVID-19's null and alternative hypotheses

   Null Hypothesis 3. *DISP-RATIO*$_{iCOVID-19} \geq DISP - RATIO_{iNot'COVID-19}$

   Hypothesis 3. *DISP-RATIO*$_{iCOVID-19} < DISP - RATIO_{iNot'COVID-19}$

The Disposition ratio (*DISP-RATIO*) is one of the two disposition effect measurements proposed by Odean (98 A). The other measurement is the disposition spread (*DISP*), which is the difference between the *PGR* and the *PLR*. On the other hand, the disposition ratio

(*DISP-RATIO*) is given by the ratio of *PGR* to *PLR* rather than the difference between the two. The disposition spread might be a good measurement to show only if funds and portfolios experience more gains than losses. However, this indicator is inappropriate for cross-fund/cross-portfolio comparisons due to a mechanical link between portfolio size and the disposition spread (see (Odean, 98 A, p.1785); and (Cici, 2012, p.802)). Therefore, to get around this matter, our paper will rely on the disposition ratio (*DISP-RATIO*) as the main measurement of the disposition effect though we believe using the disposition spread measurement might not be a big issue in our case since our analysis is focused on the most active portfolios and funds with the largest trading size in the SSM.

Lastly, the study will attempt to investigate whether the observed disposition effect experiences any significant changes in Decembers (Examining the December effect). From the literature, investors are found to significantly exhibit a preference for realizing more losses than gains in December, and such behaviour has been justified by tax considerations (Odean, 98 A; Huddart and Narayanan, 2002; Sialm and Starks, 2012; Cici, 2012). The case of Saudi Arabia is a bit different given that Saudi investors are not subject to income tax but are subject to annually pay 2.5 percent Zakat (A religious tax obligation) based on their net worth. We expect to see no difference in terms of the disposition effect in Decembers compared with the other months of the year since investors are obligated to pay their 2.5 percent Zakat on their net worth and realizing a gain and a loss will not change the amount that they are supposed to pay. Consequently, we are going to assess the null hypothesis stating otherwise, that is the disposition ratio shows significant changes in Decembers compared with the other months of the year.

Null Hypothesis 4. $DISP - RATIO_{iDecembers}$ *shows significant changes compared with the other months of the year*

Hypothesis 4. $DISP - RATIO_{iDecembers}$ *does NOT show any significant changes compared with the other months*

Detection of Disposition Effect and Its Empirical Framework

This phase of our analysis will concentrate on identifying the prevalence of the disposition effect in the daily trades of mutual funds and brokerage accounts. Basically, we divide this stage of our investigation into two steps. In the first step, we will be using a statistical approach to check if the disposition effect is present in the investors' trading behaviour. In the following step, we make an attempt to examine how the level of gains and losses affects the proportion realized for both the gains and the losses.

Odean's Statistical Approach to Detect Investors' Disposition Effect

As a first step, in order to determine the extent to which the retail brokerage accounts and the local equity mutual funds in our sample are influenced by the disposition effect, the disposition ratio, which is the dividing function of *PGR* to *PLR*, is computed for each portfolio/fund of the two investor types in the sample and at the end of each trading day. An investor that is susceptible to the disposition effect will be exposed to a high disposition ratio given he/she will excessively realize more gains than losses. By following Odean (98 A)'s approach, the computation of the *PGR* and *PLR* is defined below in equation (2.1). We run the calculations for each brokerage portfolio and mutual fund at the end of each of the trading days in our sample period in which at least one stock trade transaction occurred.

$$PGR_{it} = \frac{RG_{it}}{RG_{it} + UNRG_{it}}, \; PLR_{it} = \frac{RL_{it}}{RL_{it} + UNRL_{it}} \tag{2.1}$$

Where RG_{it} is the number or amount of capital gains realized by investor/fund i at the end of the trading day t, $UNRG_{it}$ is the number or amount of capital gains unrealized by investor/fund i at the end of the trading day t, RL_{it} is the number or amount of capital losses realized by investor/fund i at the end of the trading day t, and $UNRL_{it}$ is the number or amount of capital losses unrealized by investor/fund i at the end of the trading day t.

The cost base of each position is essential for calculating the *PGR* and *PLR* numbers and serves as a proxy for an investment's reference point at which investors assess their position whether it reflects a gain or a loss against the current market price. Although Odean (98 A), Grinblatt and Keloharju (2001), and Huddart and Narayanan (2002) determine the cost base (The reference price) as the average of the total cost of the relevant purchased stock divided by the number of the acquired shares, Frazzini (2006) employs a mental accounting approach by following the first-in, first-out (*FIFO*) accounting technique to associate a quantity of the acquired shares to its corresponding reference price. In a similar vein, Cici (2012) relies on four types of accounting method (the average cost price, first in first out (*FIFO*), high in first out (*HIFO*), and low in first out (*LWIFO*)) to estimate a stock's cost base or reference price. Therefore, given the methodological variations from earlier research and the lack of access to the comprehensive data-sets related to the investment portfolios and funds' stock holdings and their purchased prices, this empirical work will attempt to calculate the daily relative average cost price and the daily accumulative stock position balance during the whole period under the study by relying on a well-known accounting cost technique that is the last-in, first-out (*LIFO*) in order to robustly check the presence of the trading behaviour under investigation and measure the degree of disposition effect in each of the brokerage account and mutual fund in our sample.

As a first step, and after adjusting the dataset to include only sell-traceable trades, we compute the cumulative stock position balance for each trading day, as specified in equation (2.2). A trade is classified as sell-traceable if it meets one of the following two conditions: (1) the total number of shares sold across all securities within the brokerage accounts and mutual funds is always less than or equal to the total number of shares bought during the study period (2019–2021); or (2) at some point during the study period, and thereafter, the cumulative number of shares bought equals the cumulative number of shares sold. In our sample, brokerage accounts exhibit an almost complete liquidation rate—near or at 100%—while mutual funds have more variation, with a mean liquidation share of 82.2% (See Tables A.13 and A.14). By restricting our analysis to trades meeting the two criteria, which represent complete or near-complete liquidations, we effectively control for the potential confounding effect of portfolio rebalancing as the traceable positions analyzed are exited rather than partially adjusted.

$$AccumBal_{ijt} = AccumBal_{ijt-1} + VB_{ijt} - VS_{ijt} \tag{2.2}$$

Where,

- $AccumBal_{ijt}$ = Stock *j* position balance in volume in a brokerage investment portfolio/mutual fund *i* at a trading day *t*,
- $AccumBal_{ijt-1}$ = Stock *j* position balance in volume in a brokerage investment portfolio/mutual fund *i* at the previous trading day *t-1*,
- VB_{ijt} = Stock *j* Newly obtained volume in a brokerage investment portfolio/mutual fund *i* at a trading day *t*.
- VB_{ijt} = Stock *j* Newly sold volume in a brokerage investment portfolio/mutual fund *i* at a trading day *t*.

Then, after we have calculated the accumulative stock position balance for each trading day, the relative average cost price[3] is determined as described in equation (2.3).

[3] When comparing active brokerage accounts and mutual funds, a key distinction emerges in their intraday versus end-of-day trading behaviour, which has significant implications for how trading costs are assessed relative to a reference price. Active brokerage accounts—especially those using specialized or high-frequency strategies—generally place trades continuously throughout the day, reacting to short-term price movements, volatility trends, and changes in market liquidity (Barber et al., 2009a, 2014). These strategies frequently involve intraday position turnover, which makes volume-weighted average prices more appropriate benchmarks for evaluating execution costs (Zarattini and Aziz, 2023; Mitchell et al., 2020). In contrast, actively managed mutual funds operate with longer investment horizons and tend to concentrate their trading activity near

$$RAC_{ijt} = \frac{AccumBal_{ijt-1} \ \times \ RAC_{ijt-1} \ + \ VB_{ijt} \ \times \ BP_{ijt}}{AccumBal_{ijt-1} \ + \ VB_{ijt}} \tag{2.3}$$

Where,

- RAC_{ijt} = Stock *j* relative average cost price in a brokerage investment portfolio/mutual fund *i* at a trading day *t*,
- RAC_{ijt-1} = Stock *j* relative average cost price in a brokerage investment portfolio/-mutual fund *i* at the previous trading day *t-1*,
- BP_{ijt} = Stock *j* purchased price in a brokerage investment portfolio/mutual fund *i* at a trading day *t*.

Once the daily accumulative stock position balance ($AccumBal$) and the daily relative average cost price (RAC) are computed and determined, we, then, move on to calculate and measure the proportion and the position realized whether a profit or a loss of each sell transaction occurred in all of the brokerage accounts and mutual funds in our sample. After doing so, we identify the proportion of gain realized as *PGR* and the proportion of loss realized as *PLR*.

In terms of computing the disposition effect, this study utilizes the disposition ratio ($DISP - RATIO$) introduced by Odean (98 A) and relies on it as a measure of the disposition effect when conducting a cross-sectional analysis between investors/funds. This measure is given by the proportion of capital gains realized (*PGR*) to the proportion of capital losses realized (*PLR*) and specified in the following equation (2.4).

$$DISP - RATIO_{it} = \frac{\mu(PGR)_{it}}{\mu(PLR)_{it}} \tag{2.4}$$

Where,

- $DISP - RATIO_{it}$ = The disposition effect measure observed in a brokerage investment portfolio/mutual fund *i* at time *t*,
- PGR_{it} = The corresponding mean for the *PGR* observed in a brokerage investment portfolio/mutual fund *i* at time *t*,
- PLR_{it} = The corresponding mean for the *PLR* observed in a brokerage investment portfolio/mutual fund *i* at time *t*.

the market close, aligning with end-of-day net asset value (NAV) calculations (Goetzmann et al., 2001). This divergence in trading patterns and reference price selection highlights the importance of aligning cost benchmarks with investor type in order to accurately assess trading behaviour, including the disposition effect.

Examining the Level of Gains and Losses with the Proportion Realized

Although Odean (98 A)'s approach has a clear framework for tracking the disposition effect phenomenon in stock markets as well as has served as a useful baseline for many subsequent studies (Chen et al. (2007), Barber et al. (2007), Barberis and Xiong (2009), and Cici (2012)), it focuses on evaluating the overall presence of the disposition effect in the stock sell trades under investigation presuming that every sale choice is independent.

Therefore, as an additional assessment, this paper suggests the following regression specifications described in equation (2.5) to further explore how the magnitude of capital gains and losses affects the proportion realized for both the brokerage accounts and mutual funds in our sample. The main advantage of using a regression model is that it allows for more control over the standard errors that can be clustered to avoid assuming that each sell transaction is independent. Furthermore, a number of demographic characteristics including gender, age, education level, investing experience, income, and occupation, and whether a fund is managed by a team or individually, could be utilized as controlling variables to improve the estimation of the regression model. However, the study was unable to incorporate the investors/funds' demographic characteristics into its regression model due to the sensitive and confidential nature of such data.

$$PrReliz_{ijt} = \alpha_i + \beta_1 |Ret_{ijt}| \cdot Gain_{ijt} + \beta_2 |Ret_{ijt}| \cdot Loss_{ijt} + \epsilon_{ijt} \tag{2.5}$$

Where,

- $PrReliz_{ijt}$ = the proportion realized from the overall holdings for investor/fund i and stock j in a trading day t.
- $|Ret_{ijt}|$ = the absolute obtained return for investor i and stock j in a trading day t.
- $Gain_{ijt}$ = a dummy variable that equals 1 if the stock j for investor i is sold in a trading day t at a gain and 0 otherwise.
- $Loss_{ijt}$ = a dummy variable that equals 1 if the stock j for investor i is sold in a trading day t at a loss and 0 otherwise.

The intuition behind estimating this model is to measure the impact of stock gains and losses magnitude on the stock proportion realized for the two types of investors under investigation. Both *Gain* and *Loss* are dummy variables interacting with the stock absolute obtained return |*Ret*| in order to see how the level of both gains and losses affect the investors' disposition trading behaviour. For example, if the observed coefficients are negative, this means investors are reluctant to increase the activity of selling their holdings with an increase observed in the level of gains and losses. However, if the observed coefficients are positive, it means investors are prone to increase the activity of selling their holdings with an increase observed in the level of gains and losses. Thus, within this estimation, we believe we will be able to identify how investors' disposition trading behaviour responds to any change observed in stock gains and losses.

Disposition Effect Investigation during Ramadan and COVID-19 Pandemic

After assessing the disposition effect in the trading records of our sample, the present study aims to examine the trading patterns of the disposition effect before and after specific time periods such as the holy month of Ramadan and COVID-19 pandemic. More specifically, this empirical work will be focusing on a panel event study approach given that we seek to reveal the impact of the arrival of those two events (Ramadan and COVID-19 Outbreak) on the disposition trading behaviour among retail and professional investors in the SSM. The event study technique is considered one of the most well-known and suitable approaches to evaluate how a single identifiable event impacts the investors' behaviour throughout its entire course. In fact, forecasting how investors will react and respond to the announcement of an event is mostly facilitated by event studies, according to Anwar et al. (2017). Thus, the announcement of an event, such as in our case the entrance of the holy month of Ramadan and the outbreak of COVID-19 pandemic, might impact the stock markets, in general, and the investors' disposition trading behaviour, in specific, either positively or negatively. Mostly in the literature, the event study approach is typically used to investigate the association between a stock performance its abnormal returns, for instance, and its respective corporate events like mergers and acquisitions, splits, stock dividends, bonus shares, etc. However, several scholars such as Chen et al. (2007), Liu et al. (2020) and Pendell and Cho (2013) utilize the event study methodology to investigate how an identifiable non-corporate event, the spread of a disease, for example, influences the stock markets.

Events of Interest and their Respective Dates

The short-term impact of the COVID-19 pandemic and Ramadan season on the stock market returns has been the subject of various recent investigations (Białkowski et al., 2012; Liu et al., 2020; Zhang et al., 2020). Their main findings indicate that those two events have a significant influence on the stock market performance. In a manner somewhat comparable, this study intends to investigate the impact of these two events of interest, but on the investors' disposition trading behaviour instead of the stock market returns. The first event date we are interested to look at is the release date of the outbreak news concerning COVID-19 pandemic on the Chinese media, which is on the 20th of January 2020. On this date, the first interview about this new coronavirus disease and its transmission among people was conducted with Zhong Nanshan, the China's National Health and Fitness Commission's (NHFC) expert group leader (Liu et al., 2020). Following his interview, news of the transmitted disease caught people's attention and made headlines in print and electronic media all over the world.

The second event of interest in this study is the event of the holy month of Ramadan, which is the ninth month in the Islamic Hijri calendar. Ramadan is celebrated as a month of fasting by Muslims all over the world; it is an obligation in Islam and one of its five pillars. During their fasting and for almost 30 days, Muslims are not allowed to eat or drink anything from the sunrise to the sunset. Worth mentioning, just like the other months of the year, the trading hours in the SSM remain the same during Ramadan, which means investors make their investment decisions while fasting given that those hours are during the day time. Therefore, the second event date we are interested to look at is the 30 days period of Ramadan.

Event Study Model Specification

The event study is most likely the earliest and extremely straightforward causal inference research design. It exists before experiments and statistics. It probably existed even before human language and people. The concept is that an event happened at a particular moment, which caused a treatment to be implemented at that time. The effect of the treatment is whatever altered between before and after the incident. We shift from the "before-event" to the "after-event" at a specific point in time in which a treatment comes into effect. The term "after" in this context does not imply that the treatment comes and fads away right after that certain point in time, but rather it may still be in effect in the period following the event occurrence; therefore, we seek to quantify the impact of the treatment by contrasting the results obtained with and without the treatment (Huntington-Klein, 2021).

The actual challenging element of an event study lies on the back door and setting up the counterfactual to measure the real effect of an event. The premise that something changes over time is the foundation of an event study's entire design. The event takes place, and the treatment starts to take effect. The impact of the treatment may then be determined by comparing the before and after of the incident. However, the only thing that needs to change is the treatment. The event study won't be successful and efficient if we don't consider the possibility that the result would have changed for some other reasons. Therefore, it is very important to address and figure out a way to predict the counterfactual so that we can anticipate what we would expect to see without treatment and then observe how the actual outcome deviates from that prediction if we can assume that whatever was happening before would have continued doing its thing regardless of the treatment. The result of treatment is the magnitude of the deviation after controlling for the back door or the counterfactual.

Now, given that we are interested to estimate the impact of the investors' disposition trading behaviour undergoing two main events, the COVID-19 pandemic and the holy month of Ramadan, this empirical work will rely on following a panel event study approach, which is considered as a general extension to the difference in difference (DiD) design. Basically, we anticipate our variable of interest the disposition ratio ($DISP - RATIO$) to differ from the before the event levels and reach to new levels by the effect of the event arrival. We will be estimating the following two ways fixed effect (TWFE) model, which is specified in equation (2.6), with dynamic lags and leads. In the event of COVID-19 pandemic, we will be controlling for the investors' overall account/fund return since investors are highly driven by their performance when they sell their investments and realize their capital gains or losses. In the other event Ramadan season, we add a dummy along with the investors' account/fund return as control variable signaling for the COVID-19 pandemic restriction period from 20/01/2020 to 30/06/2020 given that the Ramadan season of this year occurs within the pandemic's restriction period.

$$DISP - RATIO_{it} = \beta_L \sum_{L=-J, L\neq -1}^{L=K} I_t(t - t_s = L) + g_t + a_i + \gamma x_{it} + u_{it} \tag{2.6}$$

Where,

- $DISP - RATIO_{it}$ = our main variable of interest the disposition ratio for investor i at time t,
- t_s = the time at which the event or treatment takes place.
- $t - t_s \Rightarrow L$ = defining each lag and lead relative to t_s.
- K = denote as the number of leads; J = denote as the number of lags.
- I_t = a set of dummy variables for each lag and lead.
- β_L = the coefficients to be plotted in the event study graph with L on the X axis and the effect degree with its reported confidence intervals in the Y axis.

- x_{it} = control variables include investors' overall account/fund return and COVID-dummy used when conducting Ramadan's event study.

- g_t = denote to the time specific effects; a_i = denote to the unit specific effects.

In terms of the dynamic leads and lags related to the first event, the COVID-19 pandemic starts in the first month of 2020. Given that we have three years in our sample, which means our event study with this regard contains 36 monthly time periods, 12 before the event or treatment takes place at time t_s and 23 time periods after the event occurred. On the other hand, when investigating the second event, the arrival of the holy month of Ramadan, which occurs once a year on the ninth month according to the Islamic calendar, so we have 8 months before the events and 3 months after the event arrival. Thus, the event study related to Ramadan will have 8 time periods before the event and 3 time periods after the event, so it covers all observations in the whole year (12 time periods in total) for three years in our sample.

2.4 Empirical Findings

2.4.1 First Investigation: Detecting the Disposition Effect in the Saudi Stock Markets

Odean's Statistical Approach Results

Table 2.2 reflects the overall results of our first investigation showing the PGR, PLR, and Disposition Ratio statistics which are computed collectively for the entire year, only the months from January to November, and the month of December stands alone for the period from January 1st, 2019 to December 31st, 2021. Brokerage accounts' findings are presented in Panel A whereas the mutual funds' results are shown in Panel B. The *t*-statistics associated with the difference in proportions (the disposition spread (*DISP*)) are also reported across all of the three periods and the two panels. Each sale that results in a gain, loss, paper gain or loss on the day of a sell transaction is counted separately and independently in these *t* tests.

From Panel A, it can be clearly seen that, for the entire year, brokerage investors do not seem to exhibit the disposition effect in their daily stock trading activity since it is equally likely for them to realize as much of gains as much of losses. In addition, as anticipated, the disposition effect in December remains at the same level as in the other months of the year since investors are subject to pay their Zakat (the religious tax obligation in Saudi Arabia) on their net worth. Hence, the null hypothesis 1, which states that $PGR_{it} \leq PLR_{it}$, cannot be rejected given that the results are statistically insignificant (a one-tailed test with a t-statistic less than 0.45) while the null hypothesis 4, which states that $DISP - RATIO_{iDecembers}$ shows significant changes compared with the other months of the year, is rejected since the results of this month have not significantly changed in comparison to the rest months of the year. Looking at the proportion realized for both the PGR and PLR in Panel A, our empirical results indicate that they are relatively high around 0.903 each, which means 90.3 percent on average of the brokerage accounts' holdings in our sample have been realized throughout the time period. This can be explained by two factors. First, the original data set shows that more than half (51.8 percent) of the purchased volumes are sold (realized) entirely on the same day of the purchase. Second, around 79.2 percent of the holdings have been sold (realized) fully in a cumulative manner throughout the time frame of the study with an estimated average holding period of 5 days (Roughly 1 week) per stock.

On the other hand, from Panel B, our empirical findings indicate that, for the entire year, mutual fund managers exhibit negative disposition spreads in their daily stock trading activity given that they show a strong preference for realizing more losses than gains. However, the strong preference for the reverse disposition effect behaviour becomes weaker in December and the difference between the PGR and PLR becomes statistically insignificant in comparison with the other months of the year. Therefore, the conclusion related to the mutual funds of this investigation is almost the same as seen in the brokerage accounts', that is the null hypothesis 1, which states the $PGR_{it} \leq PLR_{it}$, cannot be rejected whereas the null hypothesis 4 related to December effect is rejected due to the fact that the difference in proportions is statistically insignificant and that the mutual funds pay their Zakat on their NAV (Net Asset Value) and not on their annual income, which means mutual fund managers have no motivations to strongly modify their trading behaviour. In terms of the proportion realized for Panel B, the relative average PGR for the full year is around 0.298 while the relative average PLR is approximately 0.438. The estimated average holding period for the mutual funds is about 84 days (Close to 17 weeks) for each stock in their holdings.

In Figure 2.2, the monthly PGR to PLR ratio (*DISP-RATIO*) is displayed for both the mutual funds and brokerage accounts. During most months of the year, the mutual funds exhibit a *DISP-RATIO* below 0.8 whereas the brokerage accounts have a stable *DISP-RATIO* of almost 1.0. However, the Mutual Funds ratio increases dramatically in the last two months of the year to reach nearly 1.0 due to a significant decrease in PLR. From Table 2.2, the *DISP-RATIO* of mutual funds for the entire year is around 0.68 while the *DISP-RATIO* of brokerage accounts is constant at 1.0 for the entire period. This means that an average

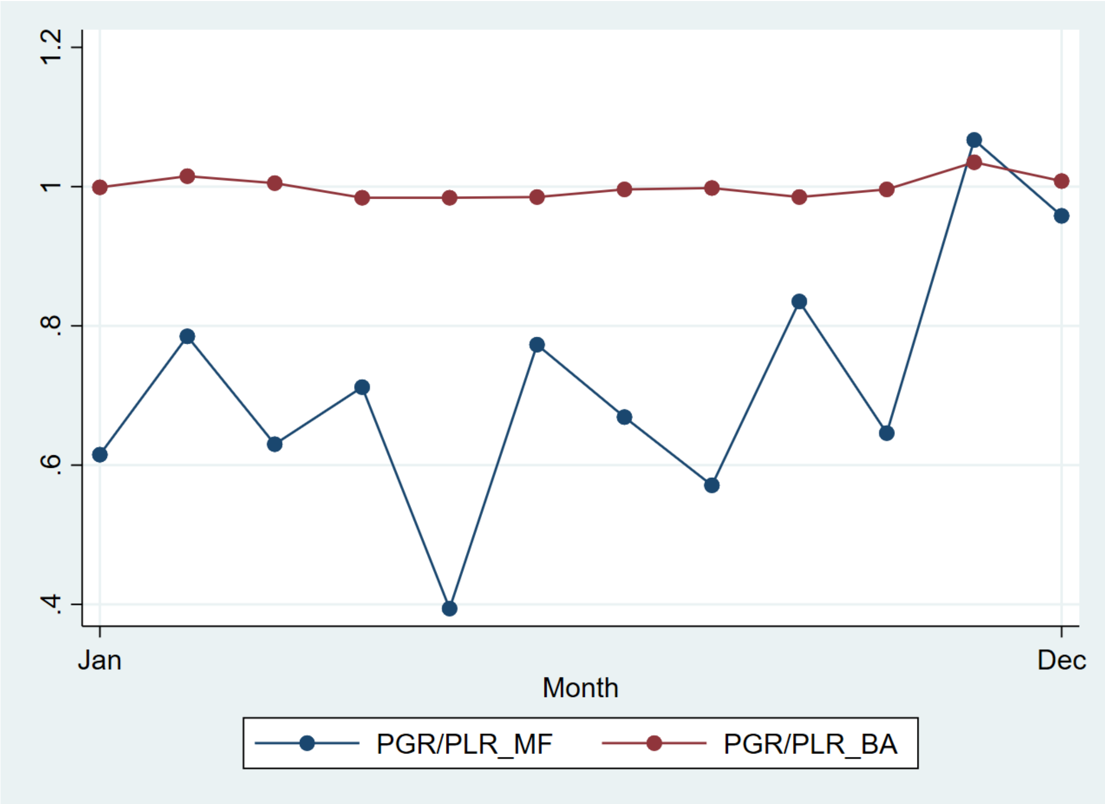


Figure 2.2: Monthly PGR/PLR (*DISP-RATIO*) for Mutual Funds and Brokerage Accounts

mutual fund manager is 1.47 more likely to realize from day to day a stock that is down in value than a stock that is up in value. On the other hand, it is equally likely for an average brokerage investor to realize either a stock appreciated in its value or depreciated from day to day.

Building on these aggregate patterns, we next examine whether there are any differences between brokerage accounts and mutual funds when trading behaviour is evaluated specifically at month-end, a period when trading decisions may be influenced by portfolio allocation adjustment, liquidity management, or other strategic considerations. Table A.15 reports the Proportion of Gains Realized (PGR), Proportion of Losses Realized (PLR), and the resulting Disposition Ratio (PGR/PLR) for both investor types over the full year and month-end trading days defined under alternative calendar frameworks.

Panel A of Table A.15 shows that brokerage accounts exhibit no aggregate disposition effect over the full sample period, with the Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR) virtually identical (0.9026 vs. 0.9033) and the difference in proportions statistically insignificant ($t = -0.45$). However, when the analysis is restricted to month-end trading days under the Islamic calendar, a modest but statistically significant reverse disposition effect emerges: investors realize approximately 1.5–1.6 percentage points more losses than gains, with t-statistics of –1.95 and –2.07 for specifications including and excluding Ramadan, respectively. This effect is absent under the Gregorian month-end framework, where the difference is smaller and insignificant. Panel B of Table A.15 presents the results for mutual funds, which display a markedly different pattern. Across the full year and in all month-end specifications, mutual funds realize a substantially higher proportion of losses than gains, producing negative differences in proportions ranging from –0.0816 to –0.1402. These differences are statistically significant in all cases, with t-statistics equal –15.64 in the full-year data. Overall, there is no significant change in trading behaviour between the full-year and month-end results, and no evidence of calendar-specific anomalies, except for a modest shift among brokerage accounts toward realizing slightly more losses than gains under Islamic month-end conditions.

With regards to the statistical significance tests observed in Table 2.2, the observations related to the sell transactions are aggregated across individual brokerage accounts and mutual funds with an assumption that each sale generates either a gain/loss, and a paper gain/loss on the trading day of the transaction is recorded individually and independently. This independence assumption might not hold perfectly. For instance, consider a case when an investor or a fund manager decides against selling the same shares on repeated occasions. The choice not to sell on one date is probably connected to the choice not to sell on a different date. Another case is when two investors or fund managers acquire the exact same information on a stock, they may be driven to sell this stock on or close to the same day. Thus, to get a better understanding of how crucial the independence assumption made at a transactional level and across all individual brokerage accounts and mutual funds, we only consider the account/fund level independence assumption to be true, which means the PGR and PLR in each account/fund are independent of those in other accounts/funds. The results of this alternative specification are presented in Table 2.3.

In Table 2.3, all of the PGR, PLR, their mean difference, and their mean ratio are estimated at the brokerage account and mutual fund level. From Panel A, we can see that the typical brokerage account's PGR/PLR for the entire year is 0.798/0.794 with an average difference and ratio of 0.004 and 1.004, respectively, while the typical brokerage account's PGR/PLR for December is 0.784/0.802 with an average difference and ratio of -0.018 and 0.978, respectively. Comparatively, from Panel B, the standard mutual fund's PGR/PLR for the full year is 0.313/0.397 with an average difference and ratio of -0.084 and 0.788, respectively, whereas the standard mutual fund's PGR/PLR for December is 0.228/0.297 with an average difference and ratio of -0.069 and 0.768, respectively. Thereby, our findings

Table 2.2: PGR, PLR and the Disposition Ratio for the Entire Data Set - At an Aggregate Level

	Full Year	December	Jan.-Nov.
Panel A. Brokerage Accounts			
$\mu_{(PGR)}$	0.90259	0.90696	0.90211
$\mu_{(PLR)}$	0.90334	0.89984	0.90372
Diff in Prop.	-0.00075	0.00712	-0.00161
$DISP - Ratio$	0.99917	1.00791	0.99822
t-statistics	-0.4453	1.3465	-0.9068
P-value (Diff in Prop.>0)	0.672	0.089	0.818
Obs.	78813	7763	71050
Panel B. Mutual Funds			
$\mu_{(PGR)}$	0.29751	0.30634	0.29674
$\mu_{(PLR)}$	0.43773	0.31986	0.45470
Diff in Prop.	-0.1402	-0.0135	-0.1580
$DISP - Ratio$	0.67967	0.95773	0.65261
t-statistics	-15.6442	-0.5078	-16.5952
P-value (Diff in Prop.>0)	0.999	0.694	0.999
Obs.	7985	747	7238

Notes. This table compares the overall Proportion of Gains Realized (PGR) to the overall Proportion of Losses Realized (PLR) across all brokerage accounts and Mutual Funds in the data set and across time (2019–2021). The *t*-statistics evaluate the null hypothesis (H_0), which states that the mean proportional differences are equal to zero under the premise that all realized gains, paper gains, realized losses, and paper losses are the consequence of separate choices.

here from this alternative specification at the account/fund level are not that far from what we have seen in Table 2.2 with the independence assumption made at the transactional level, in which we were unable to reject the null hypothesis 1, but we were able to reject the null hypothesis 4 for the brokerage accounts and mutual funds. In fact, The only difference is that the disposition effect spread/ratio for the mutual funds at the individual level on average is fairly smaller/higher for the entire period compared with what we have seen in the aggregate level investigation while it is greater/lower for December but it does not change the fact that fund managers still prefer to realize more losses than gains even in December just as seen in Table 2.2.

Although this approach might provide some insights from a different perspective, it is not exempt from some drawbacks as well since it weights each brokerage account/mutual fund equally by the number of realized/unrealized (paper) gains/losses observed in that brokerage account/mutual fund, which implies that we disregard the idea that brokerage accounts and mutual funds with more transactions produce more precise estimates of their true PGRs and PLRs. To put this in another way, by treating every brokerage account/mutual fund similarly, we make the assumption that the detected account/fund PGRs and PLRs are

Table 2.3: PGR, PLR and the Disposition Ratio for the Entire Data Set - At an Account/Fund Level

	Full Year	December	Jan.-Nov.
Panel A. Brokerage Accounts			
$\mu_{(PGR)}$	0.79771	0.78381	0.79859
$\mu_{(PLR)}$	0.79421	0.80166	0.79468
Diff in Prop.	0.00350	-0.0178	0.00391
$DISP-Ratio$	1.00441	0.97774	1.00492
t-statistics	0.22796	0.09066	0.17570
P-value (Diff in Prop.>0)	0.444	0.536	0.429
Obs.	78813	7763	71050
Panel B. Mutual Funds			
$\mu_{(PGR)}$	0.31318	0.22767	0.31717
$\mu_{(PLR)}$	0.39749	0.29659	0.40525
Diff in Prop.	-0.0843	-0.0689	-0.088
$DISP-Ratio$	0.78791	0.76762	0.78266
t-statistics	-2.3070	-0.7064	-2.2872
P-value (Diff in Prop.>0)	0.816	0.662	0.801
Obs.	7985	721	7238

Notes. This table compares the average individual Proportion of Gains Realized (PGR) to the average individual Proportion of Losses Realized (PLR) across each brokerage account and Mutual Fund in the data set and across time (2019–2021). For the entire year, only for December, and for January through November, PGR and PLR are reported. For December, the estimates are based on 16 mutual funds instead of 20 since those 16 are the only funds that have been actively trading (realizing both gains and losses) in December throughout the 3 years under study. The *t*-statistics evaluate the null hypothesis (H_0), which states that the mean proportional differences are equal to zero under the premise that all realized gains, paper gains, realized losses, and paper losses at an account/fund level are the consequence of separate choices.

homogeneous when they may really be heterogeneous. In fact, brokerage accounts and mutual funds might be homogeneous in terms of the large investment size and active investment strategy but they may not be in terms of demographic characteristics (e.g. gender, age, marital status, education level, income level, occupation and profession, connections in the investment industry, experience, and managed by a team or individually). Those demographic characteristics are not observable for both the brokerage accounts and mutual funds.

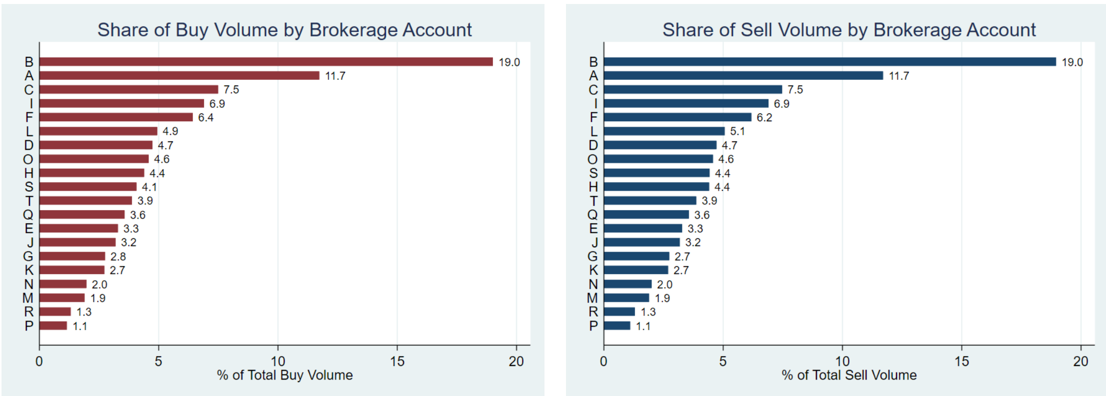
Therefore, in the following analysis, we attempt to assess the significance of unobserved heterogeneity and investigate whether it biases our results by conducting the analysis at the cross-sectional level of both brokerage accounts and mutual funds, as well as across stock market sectors. At the cross-sectional level of brokerage accounts and mutual funds, we examine both the raw trading datasets for both investors and their estimates of disposition effect across the account/fund level. The results related to the investigation of unobserved heterogeneity using the raw trade data are shown in Figures 2.3 and 2.4 while the assessment of the disposition effect is presented graphically in Figures 2.5 and 2.6, and statistically in

Tables 2.4 and 2.5.

We begin this investigation by closely examining the raw trading datasets of individual brokerage accounts and mutual funds at the account/fund level. The brokerage account data in Sub-figure 2.3a, which illustrates the share of buy volume by account, indicates that buy activity is heavily concentrated among a few dominant individual participants. Account B holds the largest share of 19.0%, followed by account A at 11.7% and account C at 7.5%. Collectively, these three accounts constitute approximately 38.2% of the total buy volume in the sample, suggesting that a concentrated group of highly active retail investors has a notable impact on overall market activity within this segment. Mid-tier accounts such as F, L, D, O, and H each contribute between 4.1% and 4.9%, while a long tail of smaller accounts has less than 3%. Sub-figure 2.3b-representing the share of sell volume by brokerage account-shows a sell-side distribution that closely mirrors the buy-side pattern, with B, A, and C again occupying the top three positions in identical proportions. This symmetry between buy and sell volumes suggests that the most active individual investors tend to engage in balanced trading behaviours rather than pursuing purely accumulative (buy-only) or liquidative (sell-only) trading strategies.

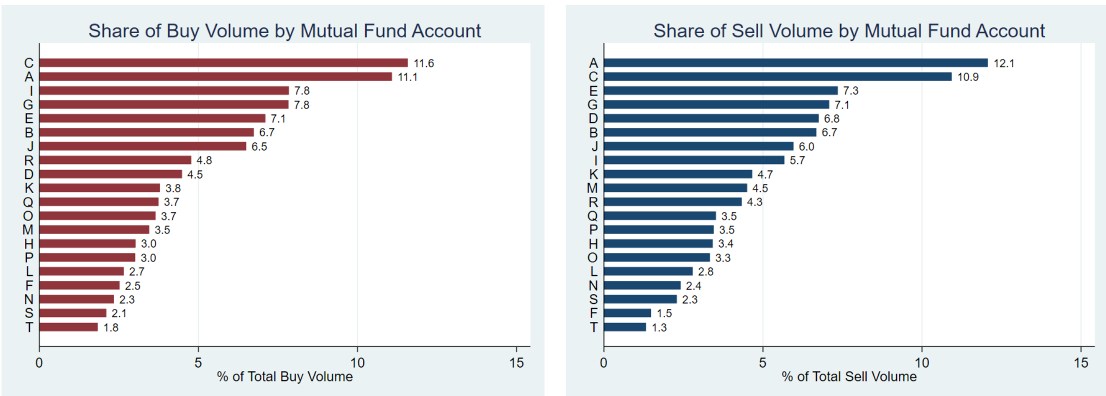
In contrast, mutual fund account activity, as shown in Sub-figure 2.4a, which describes the share of buy volume by mutual funds, presents a more even distribution of trading shares across participants. Fund C leads with 11.6%, closely followed by fund A at 11.1%, with funds I and G each holding 7.8%. While the top two funds maintain a significant presence, the decline in market share among subsequent participants is less pronounced than in the brokerage account data, indicating more dispersed participation among mutual funds. Several mid-tier funds including E, B, and J maintain shares between 6.5% and 7.1%. On the sell side, as depicted in Sub-figure 2.4b, presenting the share of sell volume by mutual funds, fund A overtakes fund C with 12.1%, while fund C drops slightly to 10.9%. Mid-tier market participants in this segment, for example, funds E, G, and D, contribute between 6.7% and 7.3%. These small but notable shifts between buy and sell rankings suggest differences in trading emphasis among the most active mutual funds, possibly linked to portfolio re-balancing activities or liquidity management needs.

When comparing the two investor categories, a clear distinction emerges in market concentration. Brokerage trading is dominated by a small set of highly active accounts while mutual fund trading activity is more evenly distributed beyond the top participants. This contrast reflects differences in market structure and decision-making processes between the two groups of investors. In brokerage accounts (Figure 2.3), the largest participants maintain nearly identical proportions between buy and sell volumes, indicating a tendency toward balanced trading behaviours that may align with short-term strategies such as swing trading, day trading, or opportunistic portfolio adjustments. In mutual funds (Figure 2.4), on the other hand, slight asymmetries are evident between buy and sell distributions. For example, fund A records a higher share of sell volume than buy volume while funds G and C change their relative rankings between the two activities. These trading patterns likely stem from the differing investment objectives and operational constraints of the two groups: individual investors may trade more frequently in response to personal market views or sentiment, whereas mutual fund managers typically follow formal portfolio strategies, adjusting holdings in line with long-term asset allocation targets, scheduled rebalancing, and investor cash flows.



(a) Share of Buy Volume by Brokerage Accounts (b) Share of Sell Volume by Brokerage Accounts

Figure 2.3: Distribution of Trading Volume by Brokerage Accounts



(a) Share of Buy Volume by Mutual Funds (b) Share of Sell Volume by Mutual Funds

Figure 2.4: Distribution of Trading Volume by Mutual Funds

Building on the insights from the investigation of raw trading data, we now turn to a more precise analysis of investor heterogeneity by assessing the disposition effect at both the individual account/fund level and across stock market sectors. This step enables us to quantify behavioural differences in trading patterns—specifically, the tendency of investors to realize gains more readily than losses—and to examine whether such differences contribute

Table 2.4: Disposition Effect Investigation by Portfolio/Fund Level

BA/MF	(a) Brokerage Accounts' Results: Diff in Prop.	t-statistic	Reject H_0	(b) Mutual Funds' Test Results: Diff in Prop.	t-statistic	Reject H_0
A	0.003	1.118	No	-0.035	-1.872	No
B	-0.043	-3.996	No	-0.050	-1.987	No
C	-0.002	-0.414	No	-0.196	-6.193	No
D	0.009	1.760	Yes	-0.116	-2.300	No
E	0.006	2.422	Yes	-0.067	-3.585	No
F	-0.049	-1.559	No	-0.128	-1.351	No
G	0.020	3.761	Yes	0.003	0.118	No
H	-0.093	-8.605	No	-0.258	-6.060	No
I	0.005	0.836	No	-0.098	-3.381	No
J	0.000	0.456	No	-0.040	-0.798	No
K	-0.152	-4.941	No	0.089	1.162	No
L	0.008	0.415	No	-0.107	-1.930	No
M	-0.007	-0.799	No	-0.087	-2.196	No
N	0.003	0.162	No	0.069	2.013	Yes
O	0.028	2.993	Yes	0.181	0.786	No
P	0.347	14.013	Yes	-0.158	-5.254	No
Q	-0.037	-5.952	No	-0.100	-3.081	No
R	0.042	2.886	Yes	-0.239	-6.516	No
S	-0.027	-0.874	No	-0.075	-2.217	No
T	0.008	0.878	No	-0.273	-1.499	No

Notes. This table shows the mean difference between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR) for each brokerage account (a) and Mutual Fund (b) along with test statistics results and the rejection decision of the H_0. The t-statistics evaluate the null hypothesis (H_0), which states that the proportional differences are equal to zero under the premise that all realized gains, paper gains, realized losses, and paper losses at an account/fund level are the consequence of separate choices.

to the unobserved heterogeneity in comparison to what was previously identified within each investor segment. The disposition effect is evaluated using both graphical and statistical approaches to capture variation across market participants and the investment contexts of each segment.

From Tables 2.4a and 2.5a and Figure 2.5, our empirical findings indicate that we observe a significant level of heterogeneity, among brokerage investors and across the sectors they invested in, with regards to the realization of their gains more than their losses given that about 30 percent (6/20) of the brokerage investment portfolios and roughly 23.81 percent (5/21) of the sectors under their investment exhibit a significant level of positive disposition spreads. However, only one brokerage portfolio shows a DISP-Ratio higher than 1.5x and one portfolio with a DISP-Ratio lower than 0.85x. From there, we tried to exclude the outliers from the brokerage sample and run the investigations again at both the aggregate and account levels. We still observe similar results indicating that even though the majority of brokerage accounts do not show strong preference toward realizing more gains than losses, some; however, (around 27.8 percent of the brokerage accounts in the sample) still show a significant level of positive disposition spreads (See Tables 2.4[4] and A.10).

In terms of the Mutual funds' findings, Tables 2.4b and 2.5b and Figure 2.6 suggest the otherwise as we observe an insignificant level of heterogeneity for mutual funds, among the funds and across their sectors, with only one fund exhibits a significant level of positive disposition spreads. However, this assessment's results confirm our previous findings with respect to the mutual funds' preferences of realizing more losses than gains as around 65 percent (12/20) of the mutual funds exhibit significant negative disposition spreads in their daily stock trading activity.

Hence, the null hypothesis 1 is rejected for six cases of the brokerage accounts and one case for the mutual fund when we run our investigation across the portfolio/fund level. In terms of the investigation across the stock market sector level, the null hypothesis 1 is rejected for five sectors for the brokerage account investments and never rejected for the mutual fund investments.

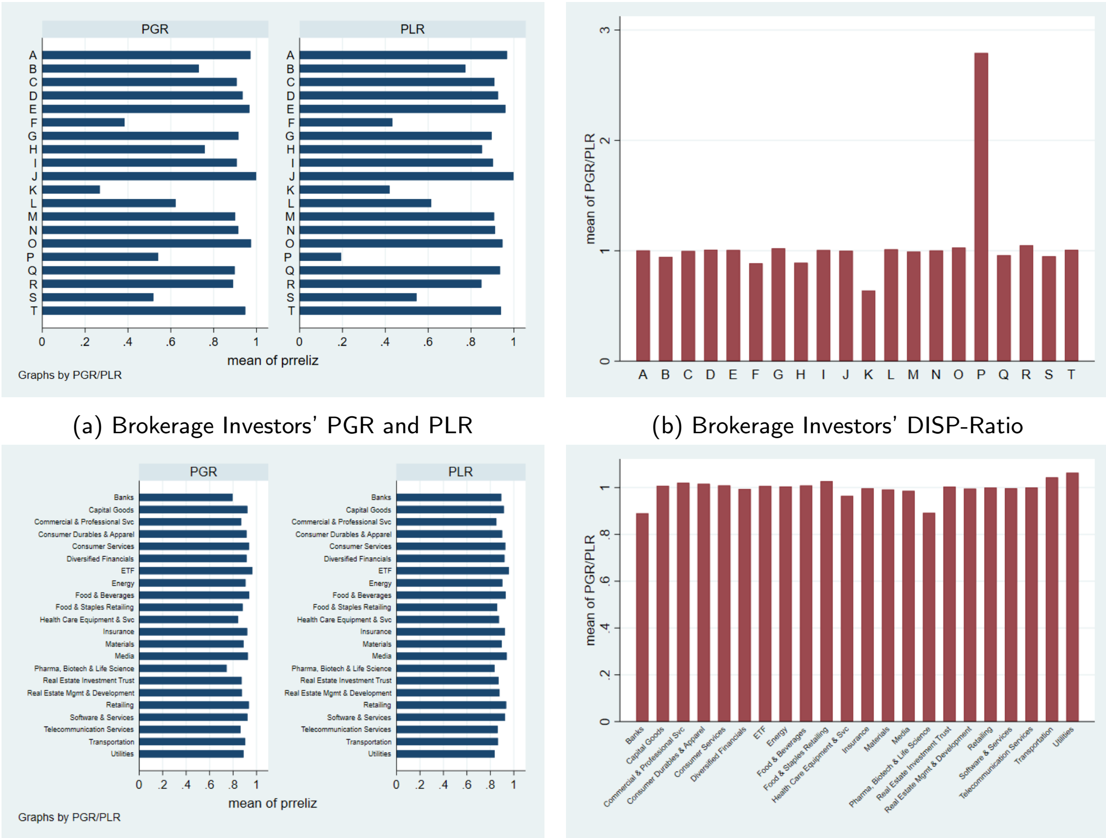
In the subsequent step, we will make an attempt to study the impact of stock investment performance on the proportion of return realized for both the brokerage accounts and the equity mutual funds in the Saudi stock markets during the period of time spanning from 1st of January 2019 to 31st December 2021.

[4] Two portfolios, K and P, were excluded from the analysis as they are considered outliers. Together, they account for 3.79% (3.88%) of the total sample's sell (buy) volumes.

Table 2.5: Disposition Effect Investigation by Sector Level

GICS Code	(a) Brokerage Accounts' Results: Prop. Diff	t-statistic	Reject H_0	(b) Mutual Funds' Test Results: Prop. Diff	t-statistic	Reject H_0
4010	-0.098	-8.047	No	-0.026	-0.705	No
2010	0.007	1.355	No	-0.098	-1.742	No
2020	0.018	1.416	No	-0.219	-2.847	No
2520	0.015	1.782	Yes	0.164	1.407	No
2530	0.008	1.498	No	-0.254	-5.575	No
4020	-0.005	-0.563	No	-0.243	-1.622	No
1010	0.007	0.149	No	-0.024	-0.693	No
3020	0.008	1.929	Yes	0.023	0.659	No
3010	0.023	1.646	Yes	-0.274	-2.332	No
3510	-0.031	-2.336	No	-0.033	-0.846	No
4030	-0.003	-0.742	No	-0.171	-4.879	No
1510	-0.007	-1.847	No	-0.203	-12.71	No
5020	-0.013	-1.373	No	-0.026	-0.176	No
3520	-0.090	-1.909	No	-0.110	-1.983	No
40401010	0.003	0.199	No	-0.207	-2.829	No
40401020	-0.004	-0.486	No	-0.039	-1.073	No
2550	0.000	0.017	No	-0.333	-8.179	No
4510	-0.003	-0.284	No	-0.093	-0.613	No
5010	0.001	0.059	No	-0.154	-3.467	No
2030	0.038	3.180	Yes	-0.134	-3.248	No
5510	0.053	3.009	Yes	-0.213	-4.202	No

Notes. This table shows the sectoral mean difference between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR) for the brokerage accounts in (a) and the Mutual Funds in (b) along with test statistics results and the rejection decision of the H_0. The t-statistics evaluate the null hypothesis (H_0), which states that the proportional differences are equal to zero under the premise that all realized gains, paper gains, realized losses, and paper losses at an account/fund level are the consequence of separate choices. The sectors are listed by GICS's (Global Industry Classification Standard) industry group codes (See Table A.5).



(a) Brokerage Investors' PGR and PLR

(b) Brokerage Investors' DISP-Ratio

(c) Brokerage Investors' Sectoral PGR and PLR

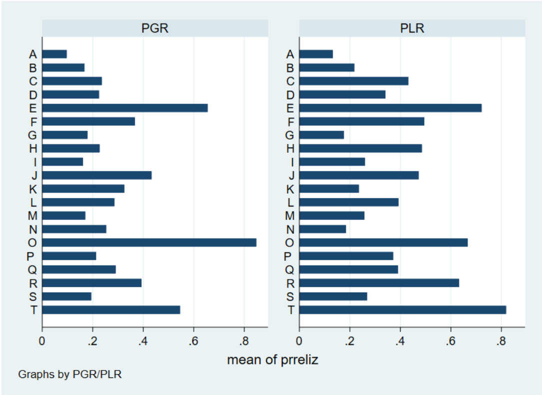
(d) Brokerage Investors' Sectoral DISP-Ratio

Figure 2.5: Disposition Effect by Stock Market Sector and Brokerage Investment Portfolio

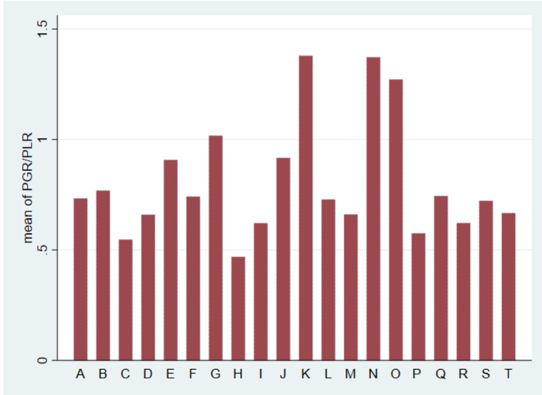
Examining How the Level of Gains and Losses Affects the Proportion Realized

Here in this section, we are going to estimate the impact of stock gains and losses on the proportion return realized. We have three-dimensional panel data sets (investor/fund i, stock j, and trading day t). The nature of our data is unbalanced. One reason for that is that certain stocks or investments may have more trading activity among investors than others, leading to an imbalance in the data across the dimension of stock j. Another reason is the randomness of investors' trading behaviour and their various investment strategies along with their different risk appetites, leading to an imbalance in the data across the dimension of investor/fund i.

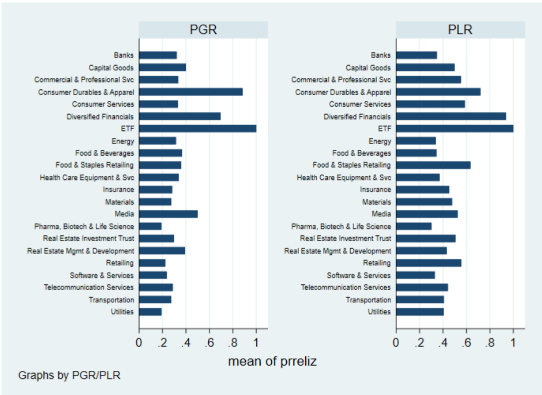
As a first step, we perform the Hausman test to discriminate between a fixed effect or random effect model and which approach is more appropriate to use in our estimation. In the Hausman test, we are testing the null hypothesis (H_0) that states that the random effect estimator is consistent and efficient as well as its coefficients are not biased. Our Hausman test results indicate that the fixed effect estimator for both brokerage accounts and mutual funds is more appropriate to use since we reject the null hypothesis (H_0) with more than a



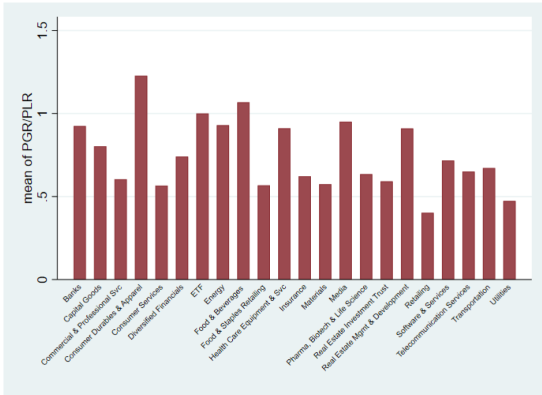
(a) Mutual Funds' PGR and PLR



(b) Mutual Funds' DISP-Ratio



(c) Mutual Funds' Sectoral PGR and PLR



(d) Mutual Funds' Sectoral DISP-Ratio

Figure 2.6: Disposition Effect by Stock Market Sector and Local Equity Mutual Fund

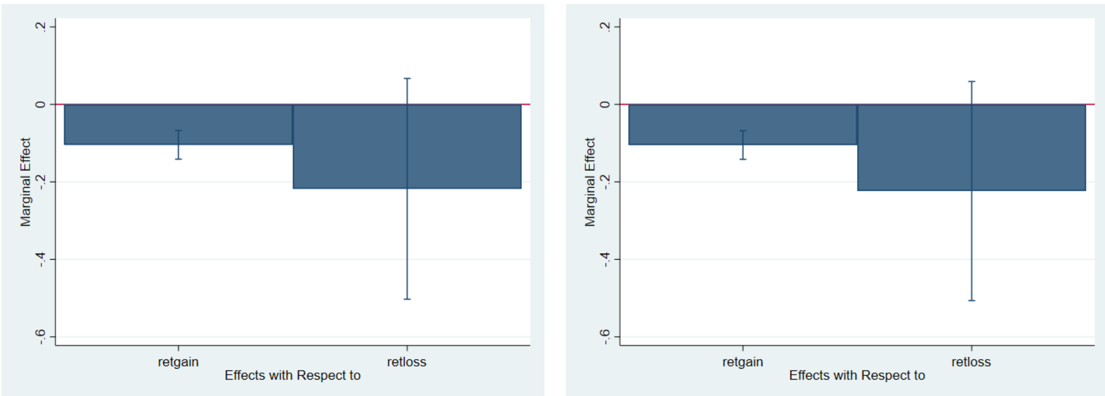
99 percent level of confidence (p-value is <0.01). Under the fixed effect estimator, the F test result also suggests that the specific unobserved individual effect a_i matters and does not equal zero, meaning that the a_i should be treated as an unobserved random variable that is potentially correlated with some if not all the explanatory variables ($cov(x_{it}, a_i) \neq 0$).

Consequently, the model specified in equation (2.5) is regressed for both the brokerage accounts and mutual funds using a fixed effect approach across account/fund and transaction level at first. Then, we run the fixed effect model again after adding the time effect to check the stability of our regression model since we are unable to include the demographic characteristics as controlling variables. The results of both estimations related to the brokerage segment are summarized in Table 2.6 and Figure 2.7. According to the regression findings in the case of no gains and losses ($retgain$ & $retloss = 0$), an average brokerage investor in our sample significantly realizes (sells) from 90 to 91 percent of his/her stock holdings. When he/she starts observing gains or losses in his/her stock investment, his/her proportion return realized will drop accordingly though the decrease is statistically significant only with stock gains (See Figure 2.7). An increase in stock gains by 1 percent will result in a decrease in the PGR by 0.1 percent.

Table 2.6: Brokerage Account Regression Results

	Dependent variable: *prreliz*	
	(1)	(2)
$retloss$	-0.218	-0.224
	(0.145)	(0.144)
$retgain$	-0.104***	-0.105***
	(0.0189)	(0.0188)
Constant	0.904***	0.912***
	(0.00530)	(0.00312)
Account & Transaction FE	Yes	Yes
Time FE	No	Yes
Observations	78,810	78,810
Clusters	3,109	3,109
R^2	0.0314	0.0250

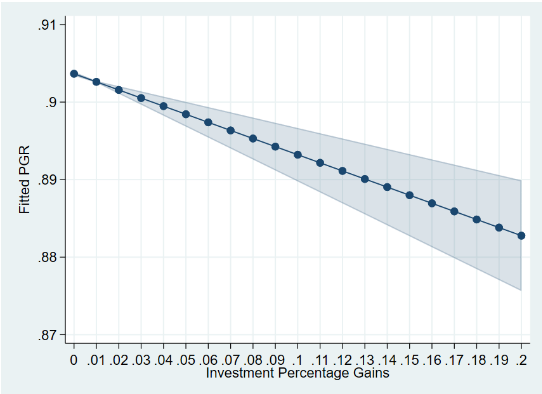
Note: Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$



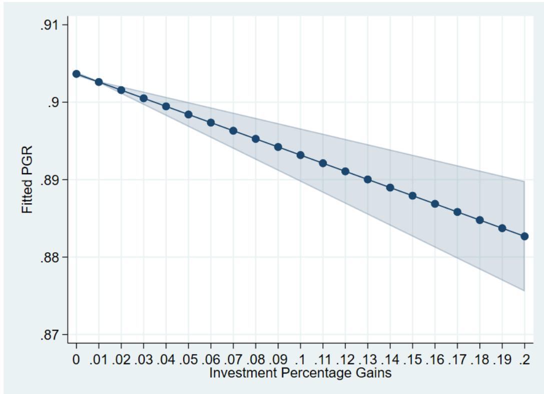
(a) Marginal Effect with *Acct. & Trans. FE* (b) Marginal Effect with *Acct., Trans. & Time FE*

Figure 2.7: Marginal Effect of $retgain$ and $retloss$ on brokerage investors' *prreliz* with 95% CIs

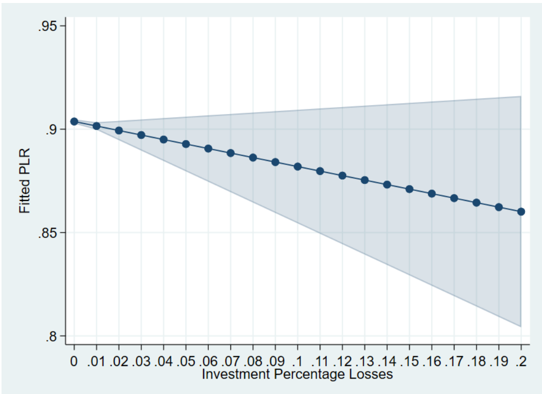
In Figure 2.8, a marginal effect projected line of PGR/PLR is fitted across various investment percentage gains/losses after controlling for account and transaction individual fixed effect shown in Figures 2.8a/2.8c as well as controlling for time fixed effect along with the account and transaction unobserved individual effect shown in Figure 2.8b/2.8d. We rely on this approach in order to robustly check the findings observed in Table 2.6 and Figure 2.7. As the investment percentage gain/loss increases, the PGR/PLR decreases though as it can be seen in the graphs and from the regression results that the case is only statistically significant with the PGR; additionally, the PGR's fitted line looks more steeper than the PLR's. Nonetheless, it can be seen that, for both cases (PGR & PLR), the confidence interval gets widened with the increase in the investment percentage gains and losses due to the fact that most of the data distribution for both the gains and the losses lies in the lowest area of the investment returns. In fact, the joint probability that a gain is realized at less than or equal to 1 percent ($P(Realized\ \cap\ x \leq 1\%)$)[5] is 71.07 percent while the joint probability that a loss is realized at less than or equal to 1 percent ($P(Realized\ \cap\ x \leq -1\%)$) is 81.32 percent. Thus, it is more likely for a gain/loss to be realized by a brokerage investor before or about reaching 1 percent showing that this investor type is highly sensitive toward stock price movement, which leads him/her to trade more frequently.



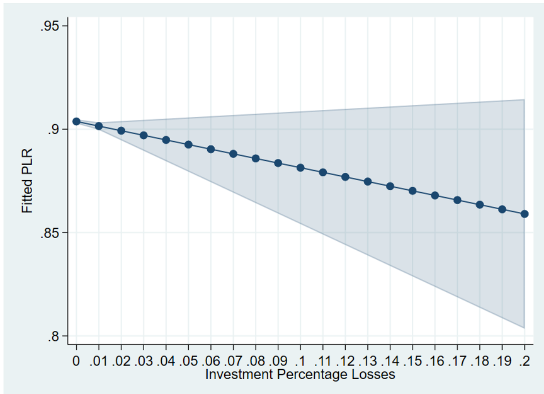
(a) PGR Fitted Line with *Acct & Trans FE*



(b) PGR Fitted Line with *Acct, Trans & Time FE*



(c) PLR Fitted Line with *Acct & Trans FE*



(d) PLR Fitted Line with *Acct, Trans & Time FE*

Figure 2.8: Fitting Brokerage Investors' PGR & PLR on Projected Line across Investment Percentage Gains/Losses between 0% to 20% with 95% CIs

Now, let us move on to discuss the results of the regression estimation related to the mutual fund segment, which are shown in Table 2.7 and Figure 2.9. According to our findings in the case of no gains and losses ($retgain$ & $retloss = 0$), an average mutual fund manager in our sample significantly realizes (sells) from 24 to 30 percent of the fund's stock holdings. When he/she starts observing gains or losses in his/her stock portfolio, his/her proportion return realized will increase accordingly. However, the level of increase toward the losses is more significant than the increase observed toward the gains (See Figure 2.9). An increase in stock losses by 1 percent will result in an increase in the PLR by 0.86 percent while an

[5] This calculation was done based on the probability distribution of the brokerage accounts' trading data where $x = stock\ return$. Please refer to Tables A.6 and A.7 for more details

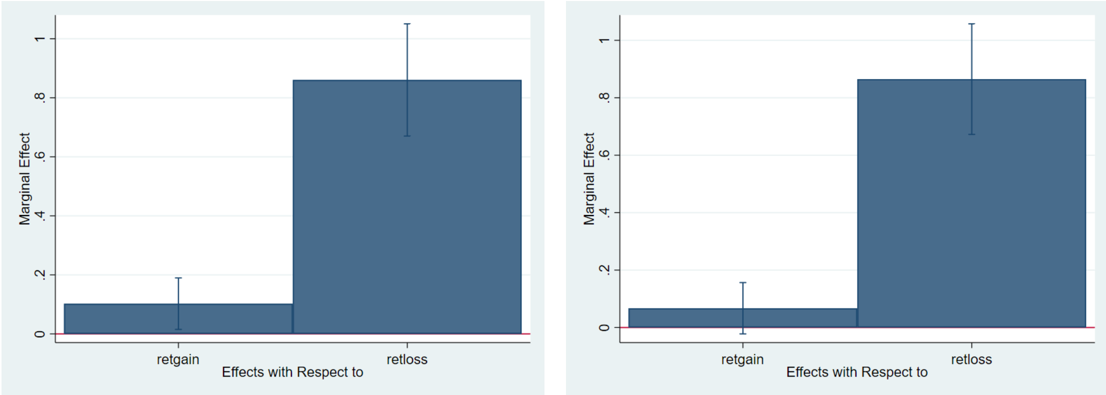
increase in stock gains by 1 percent will result in an increase in the PGR by 0.10 percent. After controlling for the time effect along with account and transaction individual fixed effect, the coefficient of $retgain$ becomes statistically insignificant whereas the coefficient of $retloss$ remains statistically significant in both models (See Table 2.7).

Table 2.7: Mutual Fund Regression Results

	Dependent variable: *prreliz*	
	(1)	(2)
$retloss$	0.861***	0.865***
	(0.0970)	(0.0983)
$retgain$	0.103***	0.067
	(0.0445)	(0.0456)
Constant	0.298***	0.235***
	(0.0077)	(0.0206)
Account & Transaction FE	Yes	Yes
Time FE	No	Yes
Observations	7,985	7,985
Clusters	834	834
R^2	0.002	0.002

Note: Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Just like the brokerage accounts to robustly check our regression findings related the mutual fund segment, a marginal effect projected line of PGR/PLR for the mutual funds is fitted across various investment percentage gains/losses after controlling for the fund and transaction individual fixed effect shown in Figures 2.10a/2.10c as well as including the time effect along with the individual fixed effect in Figures 2.10b/2.10d. As the investment percentage gain/loss increases, the PGR/PLR increases as well; however, the relationship looks more stable and clear in the case of losses even after introducing the time effect. On the other hand, the relationship changes and becomes insignificant in the case of gains after introducing the time effect. Looking at Figure 2.10, we can see that the confidence intervals are more narrow with the PLR compared to the PGR showing that the equity fund managers respond more rapidly toward stock losses by increasing the proportion realized of these losses. Given that a return (Gain/Loss) is realized, the conditional probability for this return if it



(a) Marginal Effect with *Fund & Trans. FE* (b) Marginal Effect with *Fund, Trans. & Time FE*

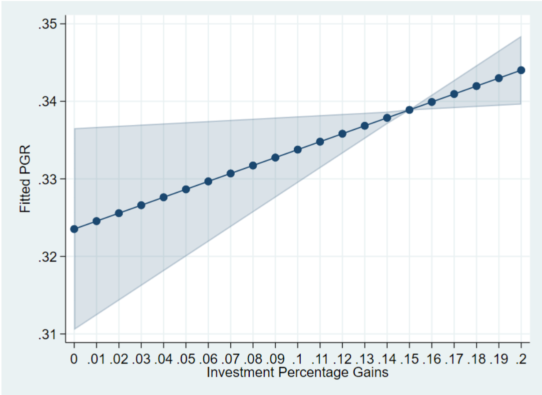
Figure 2.9: Marginal Effect of $retgain$ and $retloss$ on mutual funds' *prreliz* with 95% CIs

is a loss to be realized by a mutual fund manager at about or less than 10 percent loss $(P(x \leq -10\% \mid Realized))$[6] is 64.16 percent whereas the conditional probability for a gain to be realized at about or less than 9 percent $(P(x \leq 9\% \mid Realized))$ is 37.68 percent. Hence, we can say that a mutual fund manager is more likely to increase his/her PLR more sharply once he/she observes a stock loss while it is less likely he/she will increase his/her PGR at a similar pace when a stock gain is observed.

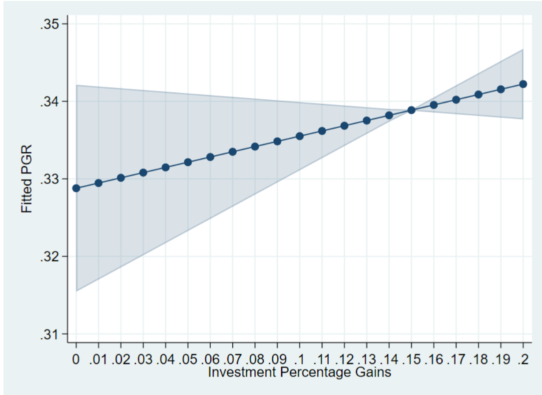
2.4.2 Second Investigation: Estimating the Impacts of Ramadan Season and COVID-19 Pandemic on the Disposition Trading Behaviour

In developing the empirical works related to this section, this paper draws inspiration from the well-crafted working framework outlined by Clarke and Tapia-Schythe (2021) and tries to follow their guidelines when constructing its event studies. In this section, we attempt to estimate the effects of our two major events—the Ramadan season and the COVID-19 pandemic— on the disposition effect trading behaviour in the SSM for the two classifications of investors—brokerage accounts and mutual funds. In the event of Ramadan, we have 8 leads prior to the event, which occurs at time (*t=0*), and 3 lags after the event. On the other hand, in the event of COVID-19 pandemic, we have about 12 leads and 23 lags. For both events, the baseline is one month before the events take place at time (*t=-1*). When running the TWFE model specified in equation (2.6), we control for investors' overall account/fund return as well as the COVID-19 pandemic restrictions period for the event of Ramadan. As for our main dependant variable *DISP-RATIO*, we attempted to replace the zero values for the PLR on the days, where investors only realize gains without realizing any losses, to 0.001

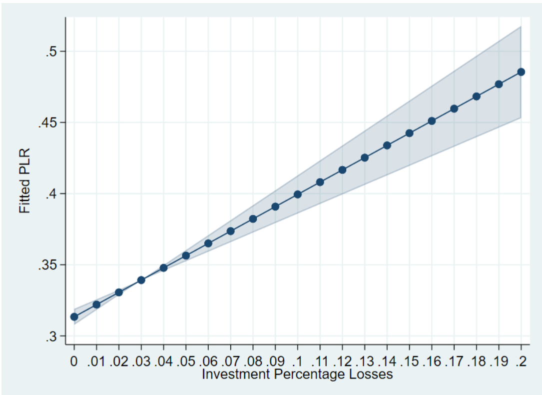
[6] This calculation was done based on the probability distribution of the mutual funds' trading data where $x = stock\ return$. Please refer to Tables A.8 and A.9 for more details



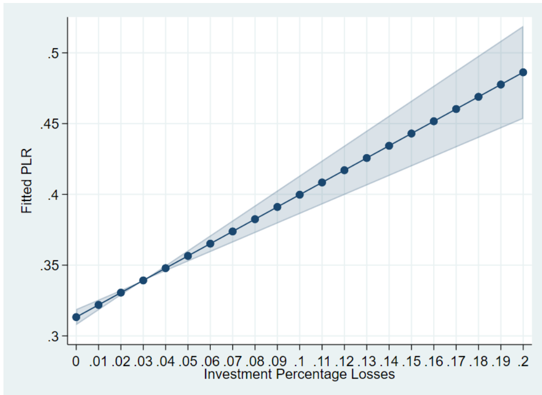
(a) PGR Fitted Line with *Fund & Trans FE*



(b) PGR Fitted Line with *Fund, Trans & Time FE*



(c) PLR Fitted Line with *Fund & Trans FE*



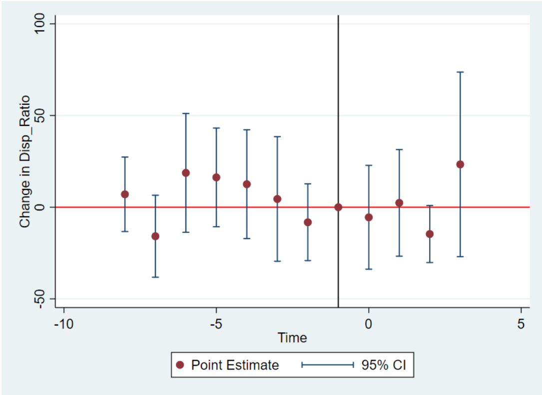
(d) PLR Fitted Line with *Fund, Trans & Time FE*

Figure 2.10: Fitting Mutual Funds' PGR & PLR on Projected Line across Investment Percentage Gains/Losses between 0% to 20% with 95% CIs

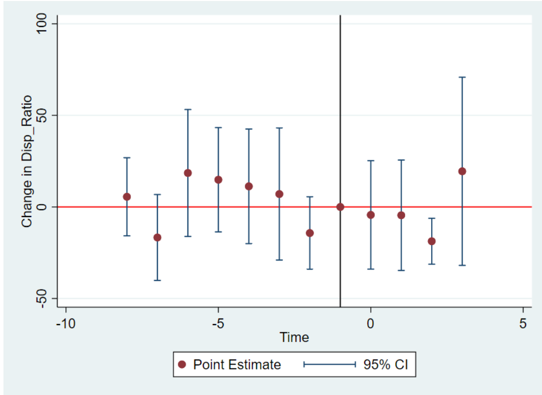
in order to be able to measure the *DISP-RATIO* and get the direction of the disposition effect on those trading days. The estimation results for both events are given in the following two subsections.

The Impacts of Ramadan Season on Brokerage Investors and Mutual Fund Managers' Disposition Trading Behaviour

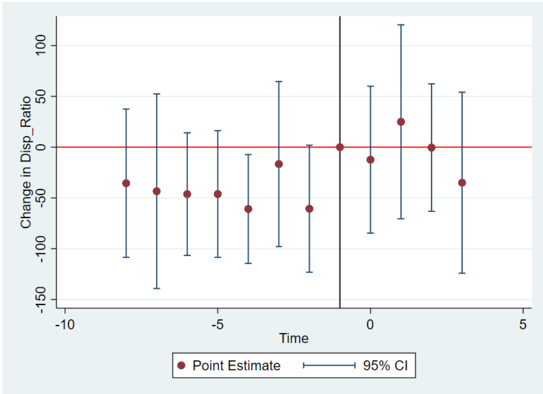
Figure 2.11 shows the impacts of Ramadan season on the investor-specific disposition trading behaviour measured by $DISP-RATIO_{it}$ across the event time. Basically, event time coefficients estimated from equation (2.6) are plotted in the figure at event time t relative to the baseline where time *t=-1*, after having controlled for investors' overall account/fund investment return and COVID-19 pandemic restrictions period. The point estimates are presented with their 95 percent confidence intervals covering 8 months before Ramadan and 3 months after Ramadan over all of the 3 years under the study. The point estimate of Ramadan is the one where time *t=0*. As shown in Figure 2.11, it can be clearly seen that Ramadan season does not significantly affect the disposition trading behaviour for both brokerage accounts and mutual funds.



(a) Brokerage Account *DISP-Ratio* - Overall



(b) Brokerage Account *DISP-Ratio* - Outliers Excluded



(c) Mutual Fund *DISP-Ratio*

Figure 2.11: Impacts of Ramadan Season on Investors' Disposition Trading Behaviour Measured by *DISP-Ratio*

*Notes.*This figure shows event time coefficients estimated from equation (2.6) for all brokerage accounts, after excluding outliers from the brokerage account sample, and all mutual funds. Point estimates are presented along with their 95% CIs. The baseline period is one month before the event (Ramadan).

However, it is worth noting that any potential effect of Ramadan could be temporary rather than persistent across the whole month. From a physiological perspective, the human body may initially experience changes in energy levels, mood, and cognitive function due to fasting, which could influence trading behaviour in the early days. As the month progresses, the body may adapt to the fasting system, leading these effects to fade. To explore this possibility, an additional test was performed using dummy variables for the first and last five days of Ramadan. The results suggest that the early Ramadan coefficients tend to be more positive, while the late Ramadan coefficients are closer to zero or even negative, although with wide confidence intervals that limit statistical significance (See Figures A.3).

To check this finding, we rerun the investigation again using the disposition spreads $DISP_{it}$ instead of the disposition ratio $DISP - RATIO_{it}$. As mentioned above, according to Odean (98 A) and Cici (2012), the *DISP* might be inappropriate for cross-fund/cross-portfolio comparisons due to a mechanical link between portfolio size and the disposition spread. However, this study includes in its sample only active investors with the largest trading size in the market. Therefore, we believe our study can utilize both measures or at least use the *DISP* as an alternative measurement for the robustness check. The results of this step are shown in the appendices in Figures A.1 and A.4. Figures A.1 and A.4 confirm the findings seen in Figures 2.11 and A.3 that Ramadan season does not seem to affect the disposition trading behaviour for both investor types-brokerage accounts and mutual funds- in the SSM. Thus, the null hypothesis 2, which states $DISP-RATIO_{iRamadan} \leq DISP-RATIO_{iNot'Ramadan}$ cannot be rejected for both the brokerage account and mutual fund investors.

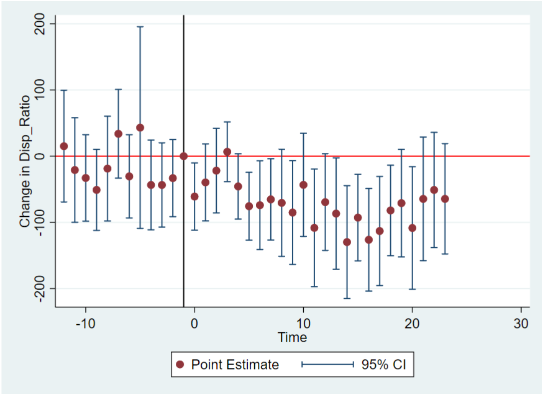
The Impacts of COVID-19 Pandemic on Brokerage Investors and Mutual Fund Managers' Disposition Trading Behaviour

Figure 2.12 plots the impacts of COVID-19 pandemic on the investor-specific disposition trading behaviour $DISP-RATIO_{it}$ across the event time line. Essentially, event time coefficients estimated from equation (2.6) are plotted in the figure at event time *t* relative to their baseline where time *t=-1*, after having controlled for investors' overall account/fund return. The point estimates are presented with their 95 percent confidence intervals covering 12 months before COVID-19 starting point and around 23 months after the starting point of the pandemic. From Figures 2.12a and 2.12b, we can see that the effect of COVID-19 on the disposition trading behaviour is clear and statistically significant for brokerage investors even after excluding the outliers[7] from the sample. The estimated event time coefficients after the arrival of COVID-19 seem to be statistically significantly lower than those estimated points before the event.

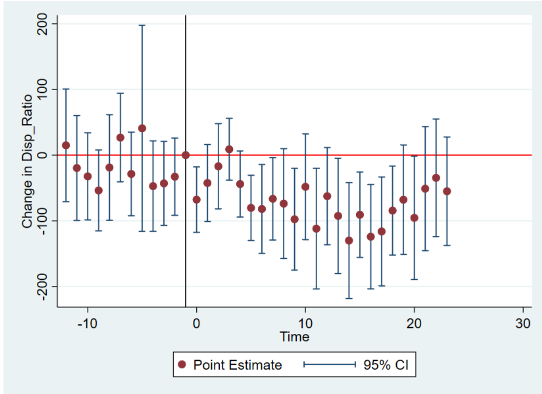
On the other hand, Figure 2.12c indicates that the effect of COVID-19 pandemic on the mutual funds' disposition trading behaviour is only statistically significant at lag 2. This estimated coefficient at lag 2 seem to be the only point that is statistically significantly lower than the baseline after the arrival of COVID-19.

To check our previous findings, we attempt to rerun the TWFE regression using the disposition spreads $DISP_{it}$ as the main variable of interest just like what we did with our previous event (Ramadan season). The related results of this assessment are presented in the appendices in Figure A.2. From Figures A.2a and A.2b, it seems that it is very difficult to assess the effect of COVID-19 pandemic on the brokerage investors' disposition trading behaviour using the disposition spreads ($DISP_{it}$) as the main variable of interest since most of the event's coefficients for both the leads and lags are significantly lower than the baseline estimated point. On the contrary, Figure A.2c confirms our previous findings related to the

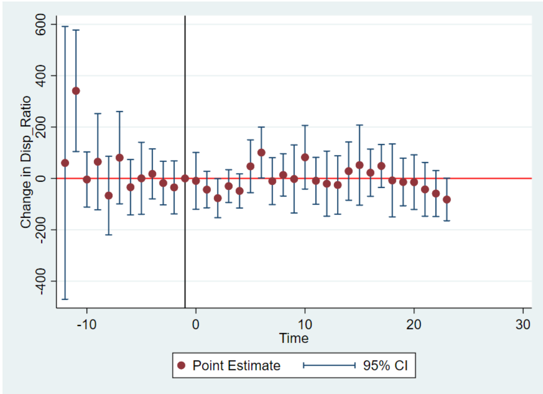
[7] Two portfolios K and P were excluded from the BA sample given that they behave extremely different compared with their peers. Together, they account for 3.79% (3.88%) of the total sample's sell (buy) volumes.



(a) Brokerage Account *DISP-Ratio* - Overall



(b) Brokerage Account *DISP-Ratio* - Outliers Excluded



(c) Mutual Fund *DISP-Ratio*

Figure 2.12: Impacts of COVID-19 on Investors' Disposition Trading Behaviour Measured by *DISP-Ratio*

*Notes.*This figure shows event time coefficients estimated from equation (2.6) for all brokerage accounts, after excluding outliers from the brokerage account sample, and all mutual funds. Point estimates are presented along with their 95% CIs. The baseline period is one month before the event (COVID-19).

event's effect on the mutual fund disposition trading behaviour seen in Figure 2.12c showing that the effect is statistically significant at both lag 2 and 3, substantially steeper at lag 2.

As a last step of this investigation, we tried to robustly check our previous findings from the event study approach by running the difference in means *t-test* for all leads and lags of the event as well as for the sub-periods before, during, and after COVID-19 pandemic restrictions period. The obtained results from this assessment are given in Tables A.11 and A.12[8]. From Sub-tables A.11a and A.11b, it can be clearly seen that brokerage investors lean significantly toward realizing more losses than gains right at the arrival of COVID-19 where time *t=0*, with *DISP*= -0.06 and *DISP-RATIO* = 0.93. The average *DISP*/*DISP-RATIO* for the sub-period after the restrictions period of COVID-19 reach to around -0.023/0.974 compared with about -0.020/0.977 for the period before the restrictions period of COVID-19 pandemic. During the restrictions period of COVID-19, The average *DISP*/*DISP-RATIO* were around 0.003/1.004, but it was statistically insignificant (See Sub-tables A.12a and A.12b). On the other hand,

[8] The tables are provided in the appendices

from Sub-table A.11c, despite the fact that mutual fund investors lean toward realizing more losses than gains, in general, the most significant and deepest point was at lag 3 after the starting point of COVID-19, where the average *DISP/DISP-RATIO* was approximately -0.35/0.47. Looking at Sub-table A.12c, this propensity toward realizing more losses continues even after the restrictions period of COVID-19. These findings of this statistical approach is almost consistent with our previous findings from the event study approach showing that COVID-19 pandemic has significantly affect the disposition effect behaviour in the SSM. Hence, the null hypothesis 3, which states $DISP - RATIO_{iCOVID-19} \geq DISP - RATIO_{iNot'COVID-19}$ is rejected for both the brokerage account and mutual fund investors.

2.5 Result Discussion and Analysis

The main findings of our investigation will be assessed and analyzed in this section, together with their importance and limitations. In the first-stage investigation, the statistical approach adopted from Odean (98 A) is done across different levels to robustly assess the presence of the disposition effect in the Saudi stock markets. The first level tests are run with the assumption that each sell trade occurs in our 40 brokerage accounts and mutual funds and results in a realized gain, realized loss, paper gain or paper loss at a trading day is considered independently and separately. In the second level, the tests are conducted with the consideration that the sell transactional independence assumption exists only on the individual account and fund level and that those accounts and funds are assumed to be homogeneous. Lastly, an assessment of the unobserved heterogeneity related to brokerage investors and mutual fund managers is conducted to evaluate if its existence biases our results obtained in the first and second specifications.

Overall, the obtained results from both the first specification with the independence assumption at the transactional level and the second specification with the transactional independence assumption at the investor/fund level provide almost the same results, in which the brokerage investors on average do not seem to be exposed to a positive or negative disposition spreads while the mutual fund managers show a strong preference toward the negative disposition spreads (Realizing more losses than gains). However, the main findings obtained from the unobserved heterogeneity assessment concerning the disposition effect existence show that brokerage investors are more likely to be heterogeneous given that around 30 percent of the detected brokerage accounts exhibit positive disposition spreads while the heterogeneity issue is considered to be less significant in the mutual fund case. This might be because the top equity mutual funds in stock markets are more likely to share characteristics, such as being managed by professional teams with high levels of experience and qualifications and sustaining a stock investment allocation process that must be approved by investment and risk management committees according to the best practice in the investment industry. On the other hand, individual brokerage investors are more likely to be diverse given their various investment styles and socioeconomic characteristics.

In addition to Odean (98 A)'s statistical approach, a regression approach is utilized to assess and estimate the impact of stock gains and losses on the stock proportion realized. For brokerage accounts, our findings show that, even in the neutral scenario, where no gain or loss is visible a typical brokerage investor prefers to realize the majority of his or her stock holdings on a daily basis. When he/she starts observing either a gain/loss, his/her PGR/PLR is reduced with a reduction rate in PLR almost twice as much as the reduction rate in the PGR though it is only significant for the PGR. In terms of the mutual funds, our results indicate that both stock gains and losses have a positive influence on the mutual funds' return proportion realized (PGR&PLR). However, the positive impact is mainly driven by stock losses since their related results are more clear and significant. From these findings, it can be seen that both brokerage investors and mutual fund managers react differently toward stock gains and losses. Brokerage investors seem to feel more reluctant to realize their losses than their gains though the losses' impact is not significant while mutual fund managers seem to increase realizing their stock losses more readily than their gains. As a result, considering the large investment size for both investors (Brokerage accounts and mutual funds) and their active investment strategies, the brokerage investors under the study can be classified as risk-averse investors with a high-frequency trading style whereas the mutual fund managers can be classified as risk-seeking investors with their investment risks under management given that they lean toward realizing stock losses in order to avoid accumulating them, which also might lead to bigger losses if the losing stocks were kept longer.

In the second investigation, a panel event study approach is used to estimate the impact of two main events-Ramadan and COVID-19-on the investors' disposition trading behaviour. By running the TWFE model twice using both *DISP-RATIO* and *DISP* as the main variables of interest, our results indicate that Ramadan season does not statistically significantly affect the disposition trading behaviour for both type of investors-brokerage accounts and mutual funds. The reason why the event impact is not significant could be that the investors only fast during the day time but can eat and drink after the sunset, during which they recover from their fasting. The fasting window is approximately from 14 to 16 hours and the eating and drinking window is from 10 to 8 hours[9].

An additional analysis was conducted to examine whether any potential Ramadan effect might be temporary, arising mainly in the early days of fasting before the body and mind adapt to the new daily routine. Using dummies for the first and last five days of Ramadan, the results showed that early Ramadan coefficients tended to be more positive, while late Ramadan coefficients were closer to zero or negative, consistent with the adaptation hypothesis. However, as in the whole-month analysis, these effects were statistically insignificant, and the associated confidence intervals were wide. This raises the possibility that the null results for both the overall Ramadan period and the early/late period tests could be due to limited statistical power or sample size constraints, rather than the absence of any underlying effect.

On the other hand when we look at COVID-19 pandemic's results using the *DISP-RATIO* as the main variable of interest, the findings show that COVID-19 pandemic has statistically significant effect on the disposition trading behaviour for both investors. However, it seems to be difficult to estimate the effect of COVID-19 pandemic on the brokerage account disposition trading behaviour using the *DISP*. The reasons for that could be one of the followings. First, the holding period for those investors is very short (5 trading days per stock); additionally, those investors realize most of their investment holdings (Almost 90 percent of their gains and losses), which means it is less likely for them to accumulate their gains and losses for long time leading them to be less exposed to sudden changes in the market. Second, our study was unable to incorporate the investors' demographic characteristics into the regression model, which could help better control the regression model and assess the counterfactual to measure the real effect of the event. Therefore, we tried to run the difference in means assessment to robustly check our findings from the event study. From this exercise, we confirm that COVID-19 pandemic has statistically significantly impacted the disposition trading behaviour for both brokerage and mutual fund investors.

Comparing our key findings with those reported in the previous literature, the result for the brokerage account segment—namely, being equally likely to realize gains and losses—appears inconsistent with the general evidence for this segment in earlier studies. However, when taking into account the sophistication[10] of the brokerage investors in our sample and their high trading frequency, our findings align with prior research (Feng and Seasholes (2005);

[9] It is similar to 16/8 daily intermittent fasting, where an individual fasts from consuming any food with calories for about 16 hours every day but eats whatever he/she likes within the remaining 8 hours.

[10] According to the Saudi Stock Exchange (Tadawul)'s classification, the majority of the brokerage accounts in our sample are classified as Qualified (Sophisticated) Investors, given that 16 out of 20 have been trading in the Nomu Stock Market, which is restricted to Qualified (Sophisticated) Investors.

Dhar and Zhu (2006); Boolell-Gunesh et al. (2012)), which shows that sophisticated individual investors—and those with large investment sizes and high trading activity—are less susceptible to the disposition effect. By contrast, our finding for equity mutual funds, indicating that their managers exhibit a substantial preference for realizing more losses than gains, is consistent with earlier results in Huddart and Narayanan (2002), Sialm and Starks (2012), Cici (2012), and Chang et al. (2016). In particular, Chang et al. (2016) demonstrate that delegating investment decisions to fund managers can reduce or even reverse the disposition effect by enabling investors to shift blame for losses, with the strength of this reversal increasing with both the degree of delegation and the level of cognitive dissonance.

Extending this comparison beyond the Saudi market, it is also instructive to examine how our results align with or diverge from evidence on the disposition effect in other emerging markets. This comparative analysis aims to shed light upon how distinct market structures, investor characteristics and behavioural tendencies shape comparable or contrasting patterns. In fact, evidence from China indicates a robust disposition effect among retail investors but with important heterogeneity by sophistication and experience. Using detailed brokerage accounts, Feng and Seasholes (2005) show that sophistication and trading experience substantially mitigate the bias—eliminating the reluctance to realize losses when combined—although the propensity to realize gains is only partially reduced. Complementing this, Chen et al. (2007) document that Chinese investors' purchase decisions underperform their sales and that they display a strong disposition effect alongside overconfidence and representativeness; however, notably, "experienced" investors are not uniformly less biased. More recently, using open-market data, Cai et al. (2018) find the disposition effect is prevalent in the A-share market but weak or absent in the Growth Enterprise and B-share segments.

Turning to India, market-level tests using index constituents show that the bias is detectable in aggregate trading level. Bharandev and Rao (2020) use 52-week highs/lows as reference points and find abnormal trading volume loads positively on the share of "winning days," consistent with disposition-driven selling pressure; ex-post, disposition-prone behaviour is associated with loss accumulation. In a broader time-series analysis, Ganesh et al. (2020) report that both overconfidence and the disposition effect are present in India, with overconfidence dominating at the market level—a pattern that helps explain elevated turnover without necessarily implying weaker disposition effect at the stock level.

Overall, the Chinese evidence seen in Feng and Seasholes (2005)'s study—where sophistication and experience mitigate the behavioural bias—aligns with our large brokerage-segment results for Saudi Arabia while the Indian findings indicate that market-level analyses can still reveal disposition effect patterns even when the sophistication of the investor base is unknown or when other behavioural biases, such as overconfidence, are more dominant.

To conclude this discussion, it is essential to recognise several limitations inherent in our empirical analysis that may restrict the scope of our findings and should be borne in mind when drawing broader inferences. One limitation is that our study concentrates only on the traceable trades included in the trading activity data obtained from the CMA. This is due to the lack of access to the investors' stock holding information which is needed to identify stock reference prices and holding positions. However, this limitation can be considered a minor issue, particularly in the case of brokerage accounts, and does not really affect our estimation since the investors under the scope of the study trade actively with high frequency. In fact, the traceable trades of brokerage accounts represent about 83.3 percent of the overall brokerage account trades included in the sample while the traceable trades related to mutual funds consist of around 55.2 percent of the overall mutual fund trades included in the sample. Another limitation that leads us to be more cautious with the interpretation of our results is that the focus of the estimation is on the most actively traded brokerage accounts and actively managed mutual funds with the largest trading size in the market and might not necessarily reflect the overall results of each investor type and his/her disposition trading behaviour in the stock market. The fact that this study concentrates on most active brokerage accounts and mutual funds is because it is a bit challenging to obtain full disclosure of investor/fund information as well as the influence of the top accounts/funds on the stock markets is higher than an average account/fund. Assessing the disposition effect in the Saudi stock markets covering a wide range of investors from each side (brokerage accounts and mutual funds) might provide better estimates but perhaps after more information is disclosed, for example, stock holding positions and the reference prices. Also, accessing investors' and mutual funds' demographic information can help the study investigates how the disposition trading behaviour varies between brokerage investors and fund managers as well as it can be helpful to better assess the event impact on the disposition trading behaviour.

2.6 Conclusion

The disposition effect is thought to be one of the most commonly observed market anomalies in financial markets. The key objective of this empirical study is to determine whether the disposition effect exists in the SSM and to investigate the disposition trading behaviour among major brokerage investors and equity mutual fund managers during two main events: the Ramadan season and the COVID-19 pandemic. By applying several statistical and regression techniques, the main findings of this study indicate the following. Major brokerage investors are found to be risk averse, highly sensitive toward stock price movement and not subject to the disposition effect. On average, it is probable that those investors will experience similar weights of realizing stock gains and losses, yet unexpectedly, a significant portion of them, almost 30 percent, are not exempted from the disposition effect. On the other hand, mutual fund managers turn out to be more of risk-seeking investors who tend to realize more losses while holding on to their gains and attempting to manage the risks associated with those decisions.

Although the statistical approach findings indicate that it is highly likely for major brokerage investors to realize an equal amount of gains and losses, the regression findings show that they respond differently when they observe stock gains and losses, placing more weight on avoiding realizing stock losses though the relationship is only statistically significant with the stock gains. In neutral terms when no gains and losses are observed, major brokerage investors realize (sell) about 90 percent of their stock holdings. However, their proportions realized (PGR&PLR) are reduced when they start observing stock gains and losses. For mutual funds, both the statistical and regression results point out that mutual fund managers are mainly driven by stock losses. In fact, the PLR will rise by around 0.86 percent for every percent increase in stock losses while the PGR will increase by 0.10 percent for every percent increase in stock gains. Still, the relationship of the PGR becomes insignificant when the time-fixed effect is introduced in our regression model.

In the second stage investigation, this research proceeded with examining the impact of two main events-Ramadan season and COVID-19 pandemic- on the disposition trading behaviour of our two types of investors (Brokerage accounts and mutual funds) for the same period under the study. In the event of Ramadan, the obtained results from the TWFE regression model indicate that Ramadan season has no statistically significant impact on the disposition trading behaviour for both types of investors. An additional test focusing separately on the first and last five days of Ramadan was also conducted to examine whether any potential impact might be temporary, occurring mainly in the early days before the body adapts to the fasting routine. The results showed a similar pattern to the whole-month analysis, revealing that coefficients for the early days of Ramadan were marginally more positive while those for the latter part of the month tended towards zero or negative values. Nonetheless, the estimates in both cases were statistically insignificant. This suggests that the null effect observed could reflect either the absence of a true effect or limitations in statistical power due to the sample size. However, using an event study approach and the difference in means t-test, we have determined that the COVID-19 pandemic has a statistically significant influence on the disposition trading behaviour of both mutual funds and brokerage accounts.

In the last part of this study, we address a minor limitation concerning our focus on the traceable trades resulting from the lack of access to the investors' stock holding information. Another limitation that is addressed in this paper is that the estimation results might not necessarily reflect the overall disposition trading behaviour but rather reflect the behaviour of the most actively traded brokerage accounts and actively managed mutual funds in the SSM with the largest investment trading size. Getting more precise estimates reflecting the overall behaviour in the market might require disclosing more information about the investors such as average cost prices, stock holding positions, and demographic characteristics. Such information could help the study better assess the presence of the disposition effect in the SSM as well as better estimate the Ramadan season and COVID-19 pandemic impacts on the investors' disposition trading behaviour.

Chapter 3

The Comparative Dynamics of Herding Behaviour: Evidence from Foreign and Domestic Investments in the Saudi Stock Market

3.1 Introduction

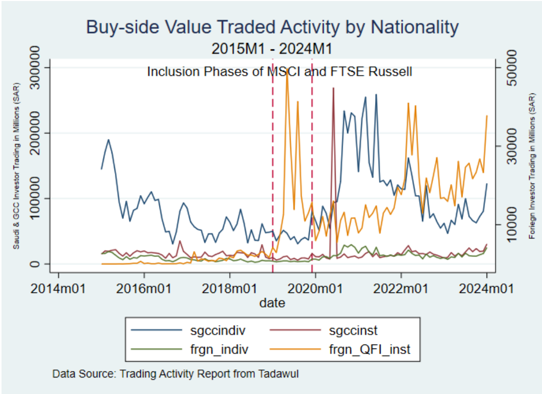
> "To understand how economies work and how we can manage them and prosper, we must pay attention to the thought patterns that animate people's ideas and feelings, their animal spirits. We will never understand important economic events unless we confront the fact that their causes are largely mental in nature."
>
> *George Akerlof and Robert Shiller*
> *(Nobel Prize Winners)*

A country's economic well-being is often reflected in its stock market performance. A consistent stock market outlook suggests that the nation's financial condition is solid and strong while an inconsistent outlook suggests otherwise. When an economy expands, it leads to higher domestic product output, which in turn increases the likelihood of businesses experiencing growth in sales and profits. On the other hand, during a recession characterized by economic decline, stock markets, acting as an indicator of economic health, tend to decrease. In fact, classical economic theory emphasizes that investment choices are driven by agents' rational expectations and stock prices reflect decisions made by efficiently utilizing all available market information including firm performance and economic outlook. However, stock prices are not always influenced solely by fundamental factors like company performance and economic indicators. Investor behaviour and market dynamics can sometimes diverge from the fundamentals, impacting stock prices in unexpected ways. As a matter of fact, several studies have demonstrated that behavioural factors are important in influencing stock market returns and prices (Scharfstein and Stein, 1990; Chen et al., 2003; Demirer and Kutan, 2006).

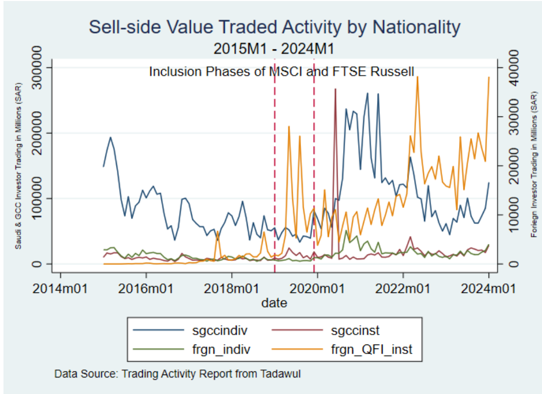
A widely accepted explanation for fluctuations in stock returns attributes price movements to the influence of herding behaviour among investors, which is often characterized as spontaneous and irrational. In the academic field of economics and finance, herding behaviour denotes a phenomenon in which economic agents and market participants imitate the actions of others, making investment decisions based on the behaviour of peers rather than relying on their own independent analysis and available information. In the context of asset pricing, the notion that herding behaviour represents an irrational reaction by investors, rather than a result of rational decision-making processing, is particularly concerning since it suggests that asset prices may deviate from their equilibrium levels (Christie and Huang, 1995). Under this premise, investors are influenced by the unpredictable dynamics of collective behaviour and may, at times, engage in transactions at suboptimal prices. This phenomenon can give rise to market inefficiencies and mispricing whereby asset values diverge from their fundamental prices due to the actions of herding investors. These investors often ignore their own private information, which can increase price distortions and contribute to greater market volatility.

Herding behaviour is widely acknowledged to occur among both institutional and individual investors and is often identified as a significant factor contributing to episodes of severe market volatility and instability. As an illustrative example, the event that occurred in November 2010, when international investors engaged in a large-scale selloff of European bonds. This led to a sharp increase in yield spreads—Spanish ten-year bond spreads rose to 5.35 percent (the highest level since 2002) while Portuguese and Irish spreads climbed to 7.23 percent and 9.42 percent, respectively—resulting in a significant drop in the euro's valuation. The previously cited quotation suggests that economic regulatory bodies, such as the European Committee on Economic and Monetary Affairs, partially attribute the market instability during this period to herding behaviour among investors (Spyrou, 2013). In the context of the U.S. stock markets, the Dot-com bubble, spanning from 1995 to 2001, is widely recognized for its extreme speculation and prevailing investor optimism. This period was characterized by irrational market dynamics with numerous empirical studies presenting substantial evidence of herding behaviour (Singh, 2013; Bergsten and Olsson, 2014). Similarly, the period preceding the 2006 crash of the Saudi Stock Market (SSM), spanning from August 2004 to January 2006, was marked by increased speculative activity. Researchers such as Alkhaldi (2015) and Lerner et al. (2017) examined the 2006 SSM crash and identified several contributing factors, including a lack of investor expertise and knowledge. Investors with limited investment experience and understanding are more prone to engage in herding behaviour (Graham, 1999; Zainul and Suryani, 2021). Balcilar et al. (2016) argue that retail investors dominate the GCC stock markets, and these investors are typically less informed, making their trading behaviour more prone to herding tendencies. Based on firm-level data from the GCC markets, including the SSM, their results show that herding behaviour tends to increase during periods of high market volatility since investors seek reassurance by following the majority view during periods of uncertainty.

As a recent development in the SSM and as a part of the capital market reforms under the Saudi Vision 2030, Saudi Arabia launched in June 2015 the Qualified Foreign Investor (QFI) program to allow foreign investors direct entry into its stock market, which is worth over $500 billion. This initiative provides international investors with an opportunity to participate in the largest economy in the Middle East. In March and June 2018, the Capital Market Authority (CMA) announced that the Saudi Stock Exchange, known as Tadawul, would join both the FTSE Russell Secondary Emerging Market and MSCI Emerging Market Indices. Alongside this announcement, the plan for anticipated inclusion was announced to take place over the next year (2019) in multiple phases. As a result of this movement, a notable shift in the distribution of buy and sell trading activities among different investor categories and nationalities was observed in the SSM (See Figure 3.1). The upward trend of QFI's buy and sell trading activities is clearly evident from the two graphs in Figure 3.1. The monthly average QFI buy (sell) value traded after Tadawul's inclusion in the EM indices reached $4.6 billion ($3.7 billion) compared to only $248.2 million ($227.7 million) before the inclusion. This resulted in a significant increase in the share of QFI buy (sell) value traded on average after Tadawul's inclusion in the EM indices to 12.6% (10.7%) compared with 1.0% (0.9%) before the inclusion.



(a) Buy-side Value Traded Activity



(b) Sell-side Value Traded Activity

Figure 3.1: Monthly Trading Activity by Investor Type and Nationality

*Notes.*This figure displays the buy-side value traded (shown in Sub-figure 3.1a) and sell-side value traded (shown in Sub-figure 3.1b) activities of four investor categories in the SSM, as obtained from Tadawul's Monthly Trading and Ownership By Nationality Reports. "sgccindiv" represents individual retail investors with Saudi and GCC nationality, "frgn_indiv" represents foreign individual retail investors, "sgccinst" is institutional investors with Saudi and GCC nationality whereas "frgn_QFI_inst" represents foreign institutional investors from the Qualified Foreign Investor (QFI) scheme.

In this research paper, my focus is on examining the impact of the redistribution of stock trades, resulting from Tadawul's inclusion in the EM indices, on herding behaviour in the SSM. This focus stems from the recognition of significant herding behaviour in the SSM as identified by several previous studies (Balcilar et al., 2013; Rahman et al., 2015; Balcilar et al., 2016; Arabi and Abdelmageed, 2022; Alnori and Ahmad, 2022). The analysis of herd behaviour in this study focuses on the market level, using the methodology introduced by Christie and Huang (1995) and further developed by Chang et al. (2000). Further discussion about the methodology used is given in the literature review and the methodology sections of this paper. The key motivation behind this research is to evaluate the policy of Tadawul's inclusion in the EM and assess its potential impact on herding behaviour within the SSM. Given the substantial size of the Saudi economy and its stock markets as being one of the largest across the globe, studying the behavioural aspects of investors in the SSM becomes crucial, as it could significantly influence stock prices and investors' performance.

This research paper will contribute to the existing literature in several significant ways. Firstly, it addresses a gap in the literature by providing a comparative analysis of herding behaviour before and after Tadawul's inclusion in the EM indices, examining both foreign and domestic investments in the SSM, an area that has not yet been explored. In fact, this study stands out as the first to investigate how the presence of QFIs has influenced herding behaviour in the SSM. Secondly, the study employs a distinct method suggested by Galariotis et al. (2015) to further explore the differentiation between "spurious" herding and "true intended" herding. "Spurious" herding refers to the type of herding that arises from common responses to fundamental information and is considered a rational behaviour. On the other hand, "true intended" herding is characterized as irrational behaviour where investors disregard their own information and base investment decisions on other investors' actions and information. The evaluation is conducted on the periods before and after Tadawul's inclusion in the EM for both QFI and domestic investments to determine the nature of herding that takes place in these distinct time frames. It is worth mentioning that researchers have only recently shifted their focus to differentiating between "spurious" and "intentional" herding (Holmes et al., 2013; Galariotis et al., 2015; Chen et al., 2017).

The remainder of the paper is structured as follows: Section 3.2 provides a summary of the literature on herding behaviour. Section 3.3 outlines the methodology and describes the dataset used in the empirical analysis. The empirical findings of the primary model including a distinction between 'spurious' and 'true intended' herding behaviour can be found in Section 3.4. Finally, Section 3.5 offers concluding remarks, discusses the study's limitations and suggests directions for future research.

3.2 Literature Review

This section focuses on establishing the research objectives by exploring psychological biases related to herding behaviour and their influence on pushing anomalies in stock returns as recognized by financial and behavioural economists. It also provides a concise literature review of herding studies in different stock markets, covering various methods used to detect this behaviour. Additionally, it ends with a brief overview of relevant literature conducted in the SSM.

3.2.1 Psychological Factors and Cognitive Biases Associated with Herding Mentality

Until the advent of rational expectation theory, which holds that independent individual economic agents are rational in that they do not consistently make errors and use all accessible information effectively, concepts centred on psychology, emotion and social influence were fundamental to many influential economic analysts. For instance, John M Keynes attributed financial instability in stock markets to the sociological and psychological forces prevailing during uncertain times. In addition to factors such as the propensity to consume from income and the desire to hold money, he highlighted waves of optimism and pessimism impacting stock markets along with the entrepreneurial drive resulting from "animal spirits". Keynes also recognized sociological influences on investors through socially driven conventions promoting speculative beliefs and actions during periods of uncertainty (Keynes, 1930, 1936, 1937). Building on this approach, other economists like Kindleberger et al. (2005) have discussed in their book titled "Manias, Panics, and Crashes: A History of Financial Crises" that the socio-psychological effects of emotional contagion by identifying speculative euphoria within groups of investors as a pivotal driver behind economic booms while excessive pessimism triggers downturns due to extreme risk aversion. From that, it becomes evident that the behaviour of investors in stock markets is influenced by a range of psychological and sociological factors. In this section, we'll explore some of the key psychological factors that drive herding behaviour in stock markets.

Informational Cascade

An Informational Cascade occurs when individuals make decisions sequentially, observing the actions of those who preceded them and disregarding their own private information. Informational cascades may not be among the main psychological factors that drive herding behaviour, yet this concept helps explain rationally why people might exhibit herding behaviour. More precisely, the terms "informational cascade" and "herd behaviour" are often used synonymously in academic literature. The key distinction between the two lies in an informational cascade, being described as a state occurring when a continuous sequence of individuals disregard their personal knowledge and insights while making a decision, in contrast to a situation where herd-like behaviour arises when a continuous sequence of individuals make identical decisions without necessarily ignoring their personal insights and information. Essentially, in herd behaviour, individuals choose the same action even though they might have acted differently if they had received different private signals. In contrast, in an informational cascade scenario, individuals consider it optimal to follow the actions of those before them irrespective of their own private signal because their belief is so strong that no signal could counterweight it. Therefore, while an informational cascade implies a herd situation, not all herds necessarily result from an informational cascade (Çelen and Kariv, 2004).

The concept of informational cascades is first introduced by Bikhchandani et al. (1992). In their proposed informational cascade model, all subsequent individuals are expected to conform to a collective decision based on public information and disregard their individual signals derived from private knowledge. This phenomenon primarily arises due to the presumption of imperfect information, as most individuals believe that those preceding them possess additional knowledge or information. Chamley (2004) theoretically demonstrates in binary settings that an informational cascade will eventually take place when there is a finite number of periods. He argues that while informational cascades are primarily a theoretical concept and do not manifest in practice due to heterogeneous signals among individuals, they offer valuable insight into social learning models. Although short-lived instances of informational cascades may occur as a temporary phenomenon, they typically cease once an individual deviates from the pattern by choosing not to follow the herd.

Social Proof

The influence of others on our actions can be classified as normative or informational. Normative impact involves adapting in order to gain recognition or approval, while informational impact occurs when we look for guidance from others in uncertain situations. Social proof is considered an example of informational influence, which can lead to herd behaviour and is also known as a heuristic (Aronson et al., 2005). The inclination to imitate others has been noted in various situations, including consumption, opinion expression, and even basic decision-making, like deciding whether to cross a street. In the field of social psychology, this conduct is described as conformity bias stemming from social influence or social proof (Cialdini and Goldstein, 2004). The strong desire to adhere to group standards is the fundamental psychological inclination that leads to herding behaviour. Several researchers in social psychology commonly conclude that majorities have a more significant impact on individual behaviour than minorities (Festinger, 1954; Deutsch and Gerard, 1955; Gardikiotis et al., 2005). In the field of behavioural finance, Shiller (1987) examines the 1987 crash in the US stock market through survey-based research. His results indicate that a majority of investors perceived the crash as stemming from other investors' psychology, and many chose to sell basically because others were doing so.

Bandwagon Effect

The bandwagon effect — also known as the "contagion effect" — occurs when individuals mimic the behaviour of others, believing that majority opinion holds greater validity. This psychological phenomenon leads people to adopt behaviours or beliefs simply because others are doing so, without considering the rationality behind their decision (Corneo and Jeanne, 1997). In the context of stock markets, the bandwagon effect influences herd mentality among investors in a way that when investors see many peers buying or selling a specific stock, they may view this collective action as an indicator of the stock's value or market direction. This perception is mostly seen during bull market conditions and can create a self-reinforcing cycle as more investors join in, further amplifying movements in stock prices. As momentum grows, even initially sceptical or cautious investors may feel pressured to follow suit to avoid missing out on potential gains or minimizing losses. Consequently, the bandwagon effect can cause exaggerated market movements and lead to bubbles or crashes as investors collectively follow trends without independently evaluating the underlying fundamentals of stocks or market conditions.

One reason for the presence of the bandwagon effect in financial markets is its function as a heuristic, enabling quick decision-making by individuals. This tendency involves bypassing extensive self-evaluation and instead relying on others' choices. The greater an idea's popularity, the more it tends to be favored, prompting more individuals to follow suit. Another contributing factor to the bandwagon effect is the fear of missing out, which also plays a role as a psychological driver of herd mentality within financial markets.

A compelling illustration of how the bandwagon effect impacts trading decisions can be seen in the case of Gamestop during 2020 and 2021. At the beginning of 2020, GameStop's stock was valued at a relatively low price, only a few dollars per share. However, towards late January 2021, there was an extraordinary surge in the stock price driven by what is known as a short squeeze phenomenon[1]. The initial incentive to invest in GME stemmed from the belief that GameStop was undervalued. This sparked a realization among a group of individual investors that there was potential for a short squeeze. As this group accumulated stocks, they aimed to drive up the stock's price sufficiently to force short sellers to repurchase their stock and limit their losses. With this information spreading across various online platforms, an increasing number of individual investors saw an opportunity not only to impact hedge funds but also potentially profit from the anticipated rise in stock prices when the short sellers reacquire their stocks. The occurrence of the short squeeze drew more retail investors into participating through bandwagon effects as they perceived the momentum building within this investment trend (Rahadi et al., 2022; Yang, 2022; Vasileiou, 2022).

Fear of Missing Out

The fear of missing out (FOMO) can impact individuals' decision-making, drawing from two key behaviours: loss aversion as proposed in prospect theory and the herd mentality. As investment decisions have a direct effect on households' financial well-being, investors tend to prioritize avoiding potential losses, known as loss aversion in prospect theory. Consequently, they may sell profitable stocks due to concerns about future price declines (Barberis and

[1] A short squeeze happens when investors who have bet on a stock's price to decrease are compelled to purchase shares in order to close their positions as the stock price surges, intensifying the upward trend.

Thaler, 2003; Dar and Hakeem, 2015). This behaviour leads to herd mentality, where investors follow others' actions to avoid missing out on opportunities. Herd behaviour relies more on public movement than private knowledge. Instead of making rational assessments based on firms' performance and financial data, investors base their decisions on collective trading choices (Caparrelli et al., 2004). The anxiety of being left behind or experiencing losses drives this phenomenon known as FOMO. Hodkinson (2019) and Dogan (2019) describe FOMO as firmly established and deeply rooted in individuals' minds, leading them to think they are overlooking an opportunity or event that others are not.

Examining the concept of FOMO in finance from a comprehensive perspective reveals its role as a key driver behind the growing participation of retail investors in financial markets. As noted by Hershfield (2020), FOMO is recognized as a major factor contributing to this increase, even during uncertain market conditions. This has resulted in a highly reactive market atmosphere, where individuals invest out of fear of missing potential opportunities. The widespread presence of FOMO among investors has been linked to the formation of speculative bubbles. In a survey-based study, Gupta and Shrivastava (2022) investigated the behaviour of retail investors in the Indian stock market and found that FOMO amplifies the effects of loss aversion and herding on investment decisions. Furthermore, other researchers have explored FOMO with various asset classes, concluding that its influence extends beyond equities (Morris, 2019; Pichet, 2017).

Safety in Numbers

Safety in numbers is considered as one of the risk management heuristics where people tend to follow the crowd due to the safety feeling they get from such action. Under certain circumstances, it is possible for the collective knowledge and expertise of individuals to be enhanced, leading to groups making more effective decisions than any single member could make alone. This concept of "collective intelligence" or "the wisdom of crowds" has been extensively explored in economics and political science and holds practical relevance in fields such as medical decision-making, management, and predictive modelling. However, when the conditions necessary for achieving collective wisdom are not present, group decision-making can exaggerate the ignorance or incompetence of individual members, ultimately resulting in poorer overall decisions compared to those made by individuals acting alone (Palley, 2016; Ebert and Morreau, 2023). Investors may experience a similar attraction, and due to their large numbers, they often tend to act more as a herd rather than a group. This behaviour can be justified since research indicates that there can be increased effectiveness and security in group activities. However, it can also lead to unfavourable outcomes, particularly in the context of online investment hype. A perfect example of the online investment hype is the Gamestop short squeeze that occurred in 2020 and 2021. This involved retail investors in the US market generating significant buzz through r/WallStreetBets, a popular online forum on Reddit focused on finance, where users exchange stock recommendations and investment forecasts.

3.2.2 Review of Different Approaches Used to Evaluate Herding Behaviour in Stock Markets

In this section, the paper will review various models utilized to assess herding behaviour in stock markets. Some studies employ a backwards-looking approach, while others adopt an innovative, forward-looking empirical framework. Within the backwards-looking methodology, researchers often quantify herding behaviour at the market-wide level, whereas others utilize high-frequency data at the micro level, focusing on trade transactions to analyze herding behaviour in stock markets. The following subsections provide a concise overview of the three different approaches.

Backward-looking Approach to Detect Herding Behaviour at Market-wide Level

This approach is widely recognized as one of the most commonly used methods in academic literature to assess herding behaviour in financial markets. In 1995, Christie and Huang (1995) introduced the concept of using return dispersion to investigate the potential presence of herd behaviour during periods of market stress. Prior to this, survey-based evidence had confirmed the existence of herd behaviour in the US stock markets (Shiller and Pound, 1986). Using a straightforward survey setting targeting institutional investors, both Shiller and Pound (1986) examined the vulnerability of institutional investors to engage in informal communication within the finance industry. Their findings revealed indications of interest contagion similar to simple epidemic models, suggesting that institutional investors are significantly influenced by their peers' actions in ways similar to epidemics.

Drawing from existing academic literature, Christie and Huang (1995)'s investigation shifts towards exploring the price implications of herding by analyzing whether equity returns indicate the presence of herd behaviour. They begin by examining how herd behaviour may be reflected in return data, under the assumption that herd formation suggests investors aligning with the consensus of the market, leading to individual returns staying close to the market return. Following this thought, the authors suggest a model to examine the herding phenomenon by evaluating how extreme market trends affect return dispersion, using the cross-sectional standard deviation of returns (CSSD) as a measure. The return dispersion measures how closely individual returns cluster around their mean value and ranges from zero when all returns move uniformly with each other and increases as individual returns deviate from this pattern [2].

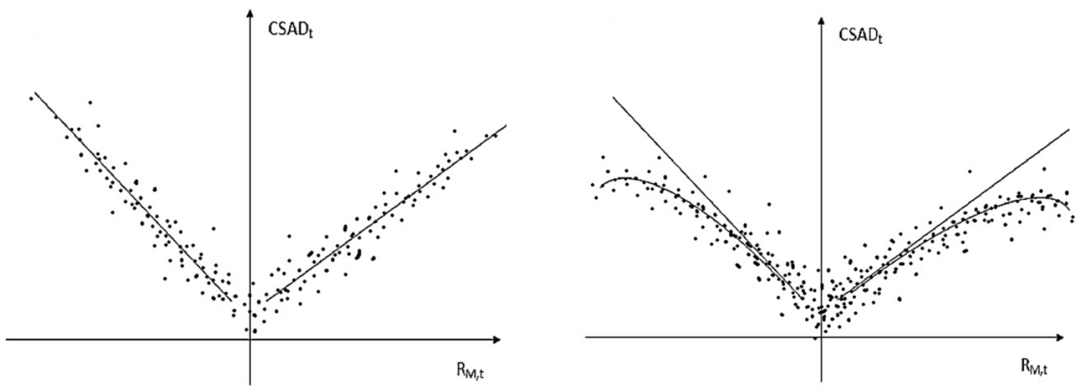
Assuming there is herding behaviour in the market, it is expected that return dispersion will decrease during periods of significant and uncommon market movements. This is because people hypothetically tend to gather around the market consensus and achieve a return very close to the market return. This expectation contradicts the rational asset pricing model, which predicts that individual returns would increase dispersion during big market movements due to differences in sensitivity to market conditions among individual financial assets. For instance, cyclical stocks are expected to be more volatile than non-cyclical (defensive) stocks and tend to mirror economic conditions, while defensive stocks are anticipated to be more stable with their performance irrespective of the state of the economy. Thus, conflicting predictions arise between herd behaviour and rational asset pricing models regarding the behaviour of dispersions during times of market stress. Assessing herding behaviour during extreme market movements, Christie and Huang (1995) found an increase in return dispersion, which is consistent with the well-established rational asset pricing model.

Building on the research conducted by Christie and Huang (1995), Chang et al. (2000) further developed the method for assessing herd behaviour. They discovered that utilizing CSSD calculations could be influenced by outliers, leading to biased results. This issue was addressed by measuring dispersion using absolute values instead[3]. In addition to this modification, Chang et al. (2000) also enhanced the model proposed by Christie and Huang (1995) and introduced a new nonlinear regression model. By deriving a corollary from Black (1972)'s Capital Asset Pricing Model (CAPM) in market equilibrium, they presumed that during normal periods without herding, expected CSAD (ECSAD) should exhibit linear correlation with market return (As can be seen in Figure 3.2a). However, in significant herding phases, individual stock returns move towards a consensus direction, indicating that the linear assumption is no longer valid (As shown in Figure 3.2b). By examining the behaviour using their approach on the US, Hong Kong, South Korean, Japanese, and Taiwanese markets, the authors found

[2] Other academic research has also employed various forms of return dispersion measurement. For instance, Bessembinder et al. (1996) utilizes the absolute deviation of individual firm returns from the market expected returns as an indication for company-specific information flows. Connolly and Stivers (1998) use the cross-sectional dispersion in the stock market to assess uncertainty related to the key fundamentals driving market dynamics. Furthermore, Stivers (1998) utilizes cross-sectional return dispersion as an indicator of uncertainty experienced by traders with incomplete information when trying to determine common factor variations based on news and price information.

[3] Through the computation of cross-sectional absolute deviation of returns (CSAD)

no significant evidence of herd behaviour in the US, Japanese, and Hong Kong stock markets. By examining their methodology in the US, Hong Kong, South Korean, Japanese, and Taiwanese markets, Chang et al. (2000) found no clear evidence of herd behaviour in the US, Japanese, and Hong Kong stock markets. However, they did uncover significant indications of herding in the South Korean and Taiwanese stock markets. Furthermore, their findings revealed that specific firm information has a less significant influence on investor behaviour compared to macroeconomic data in herding-prone markets.



(a) The Relationship as per the Rational Asset Pricing Model Predictions

(b) The Expected Relationship in a Form of Herding Behaviour

Figure 3.2: The Expected Relationship between the Return Dispersion Measured by $CSAD_t$ and the Market Return ($R_{m,t}$)

Notes. This diagram illustrates the expected connection between the cross-sectional absolute return dispersion ($CSAD_t$) and the market return ($R_{m,t}$) as per the rational asset pricing models (3.2a), and the herding behaviour theory (3.2b). The graphs have been derived from a study by Gębka and Wohar (2013).

Many researchers have utilized the frameworks put forth by Christie and Huang (1995) and Chang et al. (2000) to identify herding behaviour in various global markets. For example, Chiang and Zheng (2010) conducted a study on herding behaviour using data from 18 countries spanning daily observations from May 25, 1988, to April 24, 2009. Their findings indicated evidence of herding in advanced stock markets outside of the US as well as in Asian markets, with no evidence found in Latin American markets. Demirer et al. (2010) also examined the Taiwanese stock market and observed herding behaviour to be dominant, both in relation to the entire market and individual sectors, particularly during periods of market decline. In Europe, Ouarda et al. (2013) conducted a study on the overall European financial markets and discovered compelling indications of herd behaviour significantly contributing to a market downturn marked by high volatility and trading activity. Focusing on south European markets (Portugal, Italy, Spain and Greece), Economou et al. (2011)'s findings indicate that herding behaviour is primarily observed in the Greek and Italian markets. There is no clear evidence of such behaviour in the Spanish market, while the situation appears to be more complex for Portugal. Upon deeper examination, they discovered that herding effects exhibit notable divergences when examining upward and downward market movements, periods of high and low trading volumes, as well as volatility levels. A couple of researchers investigated the behaviour and confirmed its existence in Turkey and both class A and B stocks of Chinese markets (Kapusuzoglu, 2011; Tan et al., 2008).

Hwang and Salmon (2004) came later and introduced a new method in 2004 to identify herd behaviour at the market-wide level. They proposed that individual asset betas would deviate from their equilibrium values when investors exhibit herding behaviour, thereby reflecting changes in fundamentals. Their analysis of the US and South Korean markets revealed significant evidence of herding during major market movements. These findings are consistent with prior research such as Chang et al. (2000) and Christie and Huang (1995), which demonstrated the significance of herding both during large upward and downward market movements. Messis and Zapranis (2014) utilized the methodology of Hwang and Salmon (2004) to analyze the Greek financial market, focusing on a subset of stocks that accounted for 95% of the market capitalization of the Athens General Index. Their findings confirmed the presence of herding behaviour during the period from 1998 to 2003, as well as from early 2008 until the end of that year.

Finally, more recent research by Bohl et al. (2017) has revisited the framework proposed by Chang et al. (2000) and identified a potential misspecification in the null hypothesis underlying the model. In the original formulation, the coefficient on the squared market return is assumed to be zero in the absence of herding[4]. However, Bohl et al. (2017) show that when idiosyncratic return components are non-zero, this coefficient should theoretically take a positive value. As a result, the conventional test may, in certain circumstances, be less sensitive to actual herding behaviour and more prone to identifying "anti-herding" patterns. To address this, they propose a modified testing procedure that estimates the appropriate null value from observed market characteristics and employs bootstrap-based inference. In their empirical application to S&P500 and EuroStoxx 50 stocks, the traditional approach did not identify herding in the S&P500 and suggested anti-herding in the EuroStoxx 50 whereas the revised method found significant evidence of herding in the former and no robust evidence of anti-herding in the latter. These findings do not invalidate the usefulness of the Chang et al. (2000) approach but they do imply that findings consistent with the rational asset pricing

[4] Bohl et al. (2017) demonstrate that when idiosyncratic return components are non-zero—a realistic feature of stock returns—the relationship between $CSAD$ and the absolute market return becomes **non-linear and convex**: dispersion remains elevated for small market moves (driven by idiosyncratic noise) and then increases more rapidly for large moves (driven by differences in betas). This implies that, even without herding, the squared term's coefficient should be positive. Ignoring this leads the conventional test to be biased: it becomes less sensitive to real herding and more likely to indicate spurious "anti-herding" as seen in Chang et al. (2000)'s empirical findings.

model should be interpreted cautiously given potential biases in the original specification.

Backward-looking Approach to Detect Herding Behaviour at Trading Activity Level

This approach is considered a branch of the literature that focuses on analyzing herding behaviour and examining the level of correlation in trades among a subgroup of investors using detailed data such as portfolio holdings and trading activities. One of the earliest and widely used methods to empirically assess herding at the micro-level is the LSV empirical approach introduced by Lakonishok et al. (1992). The concept behind this empirical framework is to determine quantitatively the buying pressure on a specific financial instrument for a homogeneous segment (e.g. individual investors or institutional investors like pension funds and mutual funds). While each purchase in the overall market is matched by a sale. Within a particular segment of investors for a given financial instrument, there may be an imbalance between buy and sell orders, signifying that these investors are exhibiting herding behaviour. Following the influential work of Lakonishok et al. (1992), several empirical studies have focused on investigating herding among different types of investors, including institutional and individual traders.

The imitative trading behaviour of US mutual funds and institutional investors has been examined in various studies (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999). Similar research has been conducted in other countries, including Germany (Oehler, 1998; Frey et al., 2014), the United Kingdom (Wylie, 2005), Portugal (Lobao and Serra, 2007) and Poland (Voronkova and Bohl, 2005). The findings related to institutional investors are varied, with some research indicating only modest levels of herding (Lakonishok et al., 1992; Grinblatt et al., 1995) while others demonstrating notable herding behaviour in the institutional investors' trades (Nofsinger and Sias, 1999; Dennis and Strickland, 2002). Furthermore, herd behaviour varies among different types of institutions (Lakonishok et al., 1992); for example, pension funds exhibit less tendency to engage in herding compared to other institutions (Badrinath and Wahal, 2002). However, it is noted that most institutional herding may be spurious and not intentional (Wermers, 1999; Sias et al., 2001; Bushee and Goodman, 2007; Schmeling, 2007).

While the LSV approach has primarily been associated with institutional investors, numerous research studies have examined how individual investors imitate trading behaviour in different financial markets such as the US (Barber et al., 2009b), Germany (Dorn et al., 2008), and China (Feng and Seasholes, 2004). These studies indicate a strong correlation in the trades of individuals, showing that herding behaviour is more pronounced for individuals than for fund managers and tends to persist over time (Barber et al., 2009b). The behaviour is also found to be positively correlated with market return volatility (Venezia et al., 2011). Psychological biases have been identified as contributing factors to this herding behaviour. For example, these biases lead investors to purchase stocks with recent strong performance or abnormally high trading volume (Barber et al., 2009b). Additionally, Feng and Seasholes (2004) offers original evidence of a positive relationship between the herding behaviour of Chinese investors and their trading location.

Despite being widely used, the LSV measure has certain limitations. Specifically, it does not allow for an assessment of a specific investor's herding level and consequently is unable to estimate herding persistence across time at the individual investor level. Additionally, it is unable to explore the factors driving individual herding behaviour. Another significant critique is that the LSV measure cannot differentiate intentional herding, where investors deliberately mimic others' actions, from spurious herding, where groups with similar information make comparable decisions (Wermers, 1994; Oehler, 1998; Bikhchandani and Sharma, 2000).

Forward-looking Approach to Detect Herding Behaviour

The widespread use of social media has led to a valuable source of user-generated content on the Internet, which is beneficial for various decision-making processes and analyzing opinions on different subjects (Davis et al., 2016; Oliveira et al., 2016). Due to the quick and effective unstructured opinions expressed available on the internet, real-time evaluation enables researchers to study and understand the phenomena of herding behaviour in financial markets more accurately. This section of the literature review examines and evaluates a number of research papers that seek to use data from diverse channels on the internet to examine herding behaviour in financial markets through the applications of various novel methodologies. For example, several researchers utilize textual data from online financial forums and social media platforms to assess investor behaviour in stock markets. Ren and Wu (2018) propose a novel technique for investigating investor herding behaviour through a sentence-based sentiment analysis method. They employ a mathematical model that utilizes the constructed sentiment indices to detect herd behaviour among investors in the Chinese stock markets. The application of sentiment analysis in finance is an active area of study, aiming to identify sentiments, attitudes, and emotions from unstructured textual data sources like news publications, academic works, social media posts, and online financial forums. Through analyzing expressed sentiments in these sources, researchers can recognize patterns of herding behaviour. Ren and Wu (2018)'s distinctive approach reveals that investors with pessimistic sentiments are more inclined to display herding behaviour compared to those with optimistic sentiments. Furthermore, they indicate that macroeconomic information significantly influences decision-making processes while the lack of rapid and efficient firm-specific information leads individuals to herd around market consensus.

Other papers that explore the use of social media platforms like Twitter for assessing market movements include studies by Bollen et al. (2011), Mhanna and Sun (2020), and Mittal and Goel (2012). These studies employ sentiment analysis, econometrics, and machine learning techniques to analyze Twitter data and investigate the correlation between public sentiment and market movements. Through analyzing public sentiment on platforms such as Twitter, researchers have identified a notable correlation between public sentiment and stock market movements.

Given that Numerous studies examine the use of online textual data and sentiment analysis to identify herding behaviour in stock markets such as the papers analyzed in the previous paragraphs, others seek to understand the connections between financial news data and stock market movements. For example, Qu and Kazakov (2019) utilize text mining and statistical analysis techniques to explore the causality between financial news and the subsequent stock market movements for 25 stocks obtained from Yahoo Finance. Based on their empirical approach, a significant causal association was confirmed between financial news and market movement time series for a majority of days in the period under investigation. Similarly, Alanyali et al. (2013) analyze the link between financial news and stock market behaviour using daily issues of the Financial Times for the period from January 2nd, 2007 to December 31st, 2012 in the US stock markets. They focus on the daily company mentions in the Financial Times and daily transaction volumes of those companies' stocks in the Dow Jones Industrial Average (DJIA). Their findings indicate a notable positive correlation between the daily company mentions in the Financial Times and the daily transaction volumes of a company's stock both before release as well as on the day when it is released.

The last paper analyzed in this section explores the measurement of trading activity in financial markets using Google search volumes from the Google Trends website. Preis et al. (2013)'s research shows a significant connection between the search volume for specific financial terms on Google Trends and the fluctuations that occurred in stock market trading volume. They propose that online search patterns can offer investors useful indications about market dynamics and may be beneficial for shaping their trading and investment strategies.

3.2.3 Related Studies Conducted in the Saudi Markets

This part examines the pertinent academic works concerning the research objective, specifically herding behaviour investigations carried out within the SSM framework. Within this particular discourse, five studies are identified - Balcilar et al. (2013, 2014); Balcılar et al. (2017); Rahman et al. (2015) and Alnori and Ahmad (2022). Balcilar et al. (2013); Balcılar et al. (2017) use a Markov switching process to model the CSAD across different volatility regimes, including low, high, and extreme. On the other hand, Rahman et al. (2015) utilizes a straightforward regression analysis to estimate an expected CSAD using the beta dispersion method, whereas Balcilar et al. (2014)'s study models the herding behaviour as a transitional state. All these studies conclude that significant herding occurs, with the Balcilar et al. (2013)'s paper noting particularly intense herding during extreme market movements. The Rahman et al. (2015)'s paper finds that herding tends to intensify during upward market trends and periods of high trading volume. Furthermore, Balcılar et al. (2017) explores how speculation in the oil market influences equity herding, revealing that speculation correlates with more rational behaviours and less herding among equity markets in oil-producing countries. Unlike the previous four mentioned empirical studies, Alnori and Ahmad (2022) adopt a survey methodology to explore herding among individual investors in the SSM during the COVID-19 pandemic. Gathering data from 326 respondents, they determined that a majority of these investors in Saudi Arabia exhibited a preference for herding during the pandemic. Their study also highlights that factors such as age, gender, and educational level negatively moderate the herding behaviour among the individual investors under the study.

While these studies provide important evidence of herding in the Saudi market, they mainly focus on its existence and intensity under different conditions. Less attention has been given to the specific channels through which herding emerges, such as the growing influence of social media and the role of equity research. To address this gap, the following section examines how investment advice transmitted through these channels contributes to herding behaviour in the SSM.

Herding Behaviour in the SSM: The Roles of Social Media and Equity Research

With the expansion of the internet over the last few decades, social media has emerged as a key intermediary platform for communication among firms, analysts, and market participants. The rise of big data has further enhanced this role by accelerating investment decision-making processing. The large-scale generation of economic and financial data, coupled with the rapid spread of information and the user-friendly nature of social media, has significantly boosted communication, data sharing, and networking between users across global financial markets. In fact, a considerable number of retail investors are increasingly turning to platforms such as X (formerly known as Twitter) and Reddit for investment advice, often looking for prevailing sentiments, trends and thorough financial analysis. However, the impact of social media can amplify behavioural biases, encouraging, for example, herd behaviour that leads to unpredictable trading patterns and market volatility.

Recent evidence highlights these dynamics.Albarrak (2024) shows that platform X activity, including both the volume of corporate messages and the tone of communication, significantly influences stock returns on the SSM, with smaller firms benefiting more from message volume while larger firms are more sensitive to tone. This suggests that retail investors place considerable weight on social media sentiment when making trading decisions, thereby creating fertile ground for herd-like behaviour. Similarly, research on younger investors demonstrates that social media engagement is often driven by perceived ease of use, trust, and entertainment value rather than privacy concerns (Khan et al., 2024). These behavioural tendencies highlight how online platforms encourage reliance on peer-driven information flows even when such flows are not grounded in fundamental analysis.

Parallel patterns are also evident in equity research. Jegadeesh and Kim (2010) find that sell-side analysts frequently herd around the consensus when issuing stock recommendations. Their study demonstrates that recommendations aligned with consensus forecasts are often weaker in informational content, yet analysts may engage in such behaviour due to career concerns, reputational incentives, or the perceived safety of imitation. More importantly, markets recognize this herding behaviour by reacting more strongly toward "bold" recommendations that diverge from consensus.

Earlier theoretical and empirical work reinforces this pattern. Trueman (1994) shows that analysts often bias their forecasts toward prior earnings expectations or toward the forecasts of others even when their private information justifies more extreme estimates. This tendency reflects a reputational strategy. By staying close to the market consensus, analysts appear more accurate ex-post, thereby sustaining their credibility and client demand. Hong et al. (2000) further document that career concerns strongly shape such behaviour. Using a large dataset of earnings forecasts, they find that inexperienced analysts, who face higher risks of termination, are particularly prone to herd. These analysts tend to avoid bold forecasts, make more frequent revisions, and stay closer to the consensus, which is consistent with reputation-based herding models.

Similarly, Clement and Tse (2005) examine how personal characteristics influence herding and show that less experienced analysts and those at lower-ranked brokerage houses are more likely to conform to the market consensus forecasts. This is attributed to their greater sensitivity to reputational penalties compared with star analysts who can afford to deviate. Gallo et al. (2002) also highlight "copycat" behaviour, whereby analysts mimic each other's recommendations, contributing to common swings in target prices and clustered market reactions. Such mimicry reduces the diversity of information available to investors, increasing the risk of mispricing.

These dynamics are especially relevant for the SSM, which is dominated by retail investors who are highly influenced by social media sentiment (Albarrak, 2024; Khan et al., 2024). Retail investors tend to follow the crowd because information and opinions spread quickly and widely online, often without careful verification. At the same time, equity research also contributes to herding though in a different way. Analysts frequently align their forecasts with others to safeguard their professional standing and future career opportunities, leading to cautious, consensus-driven recommendations. In both cases, the outcome is similar. Stronger herding increases market volatility and results in prices that do not always reflect underlying fundamentals. The combination of fast-moving sentiment on social media and the consensus orientation of analyst reports reduces information diversity making it harder for financial markets to fully incorporate economic reality into asset prices.

3.3 Research Methodology and Data Description

3.3.1 Methodology and Empirical Framework

The section is organized into two empirical approaches employed in this research. Initially, the outline of the primary empirical framework used to identify herding behaviour in the SSM is described in the first part. Next, I explain the model utilized to differentiate between spurious and intentional herding by analyzing fundamental and non-fundamental information.

Return Dispersion Approach as the Main Empirical Framework to Detect Herding

Literature has divided the examination of herding behaviour into three categories or schools of thought. The first school of thought concentrates on evaluating the influence of herding behaviour on financial asset prices and returns (Christie and Huang, 1995; Chang et al., 2000). The second school of thought analyzes trading data at the transactional level, focusing on buy and sell orders executed by a specific type of investors within a given time frame (Lakonishok et al., 1992). The third school of thought utilizes activity data observed on the internet from social media channels, financial forums, and financial news websites to investigate herding behaviour in financial markets through the applications of various novel empirical approaches. The main empirical framework in this study belongs to the first school of thought as it represents the most appropriate approach given the nature of the data available[5].

As a first step, I compute all the main variables related to this part of the study. The first variable is the daily stock return, and it can calculated as specified in the following equation (3.1):

$$R_{i,t} = ln\left[\frac{P_{i,t}}{P_{i,t-1}}\right] \times 100 \tag{3.1}$$

where, $R_{i,t}$ represents stock *(i)*'s return on day *(t)*, ln is the natural logarithm, $P_{i,t}$ indicates the closing price for stock *(i)* on day *(t)*, and $P_{i,t-1}$ represents the closing price of stock *(i)* on the previous trading day *(t-1)*.

The next step involves calculating the cross-sectional equally weighted average returns of *(N)* stocks by averaging all individual stock returns on day *(t)* using the following formula specified in (3.2):

$$R_{p,t} = \frac{1}{N}\sum_{i=1}^{N} R_{i,t} \tag{3.2}$$

where $R_{i,t}$ represents the recorded stock return of company *(i)* on the trading day *(t)*, and N_t stands for the total number of companies included in the market portfolio on the trading day *(t)*.

The last variable that is used in the main empirical model is the cross-sectional absolute deviation of returns ($CSAD_t$), which is described in the following equation (3.3):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{p,t}| \tag{3.3}$$

From the equation demonstrated above, it can be seen that the $CSAD_t$ measures the extent to which an individual asset return ($R_{i,t}$) differs on average from the cross-sectional average of *(N)* stock returns in the overall market portfolio ($R_{p,t}$) at time *(t)*. Subsequently, I will elaborate more on how this dispersion measure and the return of the equally weighted market portfolios signify the herding behaviour.

After exploring the process of deriving the primary variables applied in this research, we will now proceed to discuss the key empirical model employed in this study. This paper is

[5] This research paper employs market-wide return data, for which the empirical measure of Chang et al. (2000) provides the most suitable and stable test of herding. In contrast, the Lakonishok et al. (1992) index requires investor-level transaction data, which are unavailable in this study.

based on the Christie and Huang (1995) and Chang et al. (2000)'s widely-recognized empirical frameworks for detecting herding behaviour at the market-wide level, with a specific focus on three constructed investment portfolios from the SSM as well as the time periods before and after the SSM's inclusion in the Emerging Market (EM) indices. I concentrate on these specific time frames to evaluate the impact of QFI's entry on the herding behaviour in the SSM. One of the three investment portfolios that have been constructed is the comprehensive investment portfolio, comprising all the listed stocks in the market except those not listed before SSM's inclusion in the EM indices[6]. The second portfolio comprises only the constituents of the MSCI Saudi Arabia Investable Market Index (IMI), representing 99% of Saudi's investment opportunities available for QFI. The third market portfolio consists of stocks remaining after excluding those included in the list of MSCI IM Index. Hence, the assessment of herding behaviour in the SSM will utilize three investment portfolios and cover three distinct time periods: the entire study period, before the SSM's inclusion in the EM indices, and after it. This evaluation will be conducted using Christie and Huang (1995)'s empirical model, which has been further developed by Chang et al. (2000).

At first, Christie and Huang (1995) proposed that herding in financial markets is evident in the suppression of individual beliefs, which are replaced by the market consensus. This phenomenon is particularly noticeable during periods of significant market movements, leading to greater similarity in returns across financial assets; and consequently, lower cross-sectional variability in returns. The authors recommended utilizing cross-sectional standard deviation of returns $(CSSD_t)$[7] as a main variable for identifying herd behaviour within a market environment. This dispersion measure calculates the average closeness of individual returns to the realized market average. The underlying rationale behind this measure is that when investors engage in herding behaviour, especially during extreme market movements, they tend to ignore their own opinions about individual stocks and make investment choices based solely on the collective actions of the market rather than personal judgments. As a result, if herding is present, stock returns are likely to align closely with market returns and the $CSSD_t$ is expected to be low. On the other hand, when herding is not observed, stock returns are likely to diverge from the overall market returns and the $CSSD_t$ measure is expected to be high, which is in line with rational asset pricing model predictions. This is due to the fact that rational asset pricing models indicate that stocks' sensitivity to market returns, known as betas, varies among different firms. Therefore, periods of significant market fluctuations are expected to lead to greater dispersion.

[6] These stocks are excluded in all of the three constructed investment portfolios analyzed in this research.

[7] That is given by $\sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{p,t})^2}{N-1}}$

To distinguish between the two conflicting hypotheses proposed by herding behaviour and rational asset pricing models, Christie and Huang (1995) set apart the level return dispersion for individual stocks ($CSSD_t$) in the extreme tails of the market returns distribution using dummy variables. They examined if these levels varied notably from the mean dispersion levels (excluding outliers) by estimating the linear regression model specified in equation (3.4).

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{3.4}$$

where $D_t^L = 1$ when the market portfolio return at time t is in the extreme lower tail of the distribution, and 0 otherwise. In the same manner, $D_t^U = 1$ if the market portfolio return at time t lies in the extreme upper tail of the distribution, and 0 otherwise. These two dummy variables D_t^L and D_t^U attempt to capture variations in return dispersion during periods of market stress.

From Christie and Huang (1995)'s regression model expressed in equation (3.4), the coefficient α represents the average dispersion of the sample after excluding the areas covered by the two dummy variables D_t^L and D_t^U. If β_1 and β_2 are negative and statistically significant, this signifies the presence of herding behaviour as the coefficients imply a decrease in returns dispersion during times of market stress. On the other hand, positive and statistically significant β_1 and β_2 would align with rational asset pricing models as they reveal an increase in returns dispersion during periods of market stress.

The concept of testing for herding by comparing the dispersion of observed returns with predicted ones was expanded and further developed by Chang et al. (2000). They replaced the $CSSD_t$ with the $CSAD_t$ to measure return dispersion since the $CSAD_t$ is considered to be highly sensitive to outliers. They illustrate that the cross-sectional absolute deviation of stock returns ($CSAD_t$), described in equation (3.3), is a linear function of market portfolio return ($R_{p,t}$) presuming that stock returns adhere to a model like the well-known Black (1972)'s CAPM. This relationship is illustrated in Figure 3.2a. The authors also suggest that during periods of financial distress when absolute market returns are high, it is more likely for the market participants to herd and follow the market, leading to a reduction in return dispersion and resulting in downward deviations of $CSAD_t$ from its linear relationship with $R_{p,t}$. Their regression model is specified in the following equation (3.5).

$$CSAD_t = \alpha + \gamma_1 |R_{p,t}| + \gamma_2 R_{p,t}^2 + \epsilon_t \tag{3.5}$$

In this model, if herding behaviour exists, we anticipate a nonlinear association between the dispersion measure $CSAD_t$ and the returns of equally weighted market portfolio $R_{p,t}$. Consequently, the coefficient γ_2 is expected to be negative and statistically significant (as illustrated in Figure 3.2b). However, following Chang et al. (2000), the baseline test assumes that in the absence of herding the $CSAD$–market return relation should be linear, implying that the squared term coefficient, γ_2, is statistically indistinguishable from zero. Nonetheless, as Bohl et al. (2017) argue, idiosyncratic return components naturally induce a convex relation even without herding, which implies that treating $\gamma_2 = 0$ as the null may lead to biased inference, specifically by underestimating the presence of herding and overstating the likelihood of anti-herding. In light of this, findings where γ_2 is not significantly different from zero are interpreted here in this paper as inconclusive rather than as definitive evidence of no herding.

Two models specified in equations (3.6) and (3.7) have been introduced by Chang et al. (2000) to distinguish between positive and negative market returns.

$$CSAD_t^D = \alpha^D + \gamma_1^D |R_{p,t}^D| + \gamma_2^D (R_{p,t}^D)^2 + \epsilon_t \tag{3.6}$$

$$CSAD_t^U = \alpha^U + \gamma_1^U |R_{p,t}^U| + \gamma_2^U (R_{p,t}^U)^2 + \epsilon_t \tag{3.7}$$

where $R_{p,t}^D$ and $R_{p,t}^U$ represent the cross-sectional averages of N stock returns in the market portfolio at time t, during downward and upward market movements, respectively[8]. These two specifications, similar to the general model in equation (3.5), identify herding when the estimated γ_2 coefficient is negative and statistically significant, capturing the expected non-linearity. It is important to note, however, that under the null hypothesis of no herding, the squared-term coefficient γ_2 in the Chang et al. (2000) model should be positive rather than zero, owing to the effect of idiosyncratic return components on the CSAD–market return relationship as argued by Bohl et al. (2017). Accordingly, this study interprets significantly negative estimates of γ_2 as directional evidence of herding while treating $\gamma_2 \geq 0$ as inconclusive rather than as evidence of "no herding" or "anti-herding."

This research paper aims to employ the three regression models described in equations (3.5), (3.6) and (3.7) to detect herding behaviour in the SSM at a market-wide level over the entire period under investigation, as well as during downward and upward market movements. This will be achieved by using three different investment portfolios (the portfolio

[8] To distinguish between positive and negative market returns, the equations specified in (3.6) and (3.7) can be restated as $CSAD_t = (\alpha^D + \gamma_1^D |R_{p,t}^D| + \gamma_2^D (R_{p,t}^D)^2 + \epsilon_t) \cdot (1 - UP_t) + (\alpha^U + \gamma_1^U |R_{p,t}^U| + \gamma_2^U (R_{p,t}^U)^2 + \epsilon_t) \cdot UP_t$, where $UP_t = 1$ if $R_{p,t} > 0$ and zero otherwise.

of all listed shares in the market, the MSCI investment portfolio representing 99% of QFI investments in the SSM along with local investments, and the domestic investment portfolio consisting of remaining stocks that only available for local investors) to assess the impact of QFI entry on the existing herding behaviour within the SSM. To gauge this impact, I identify the start of the year 2019, in which the SSM's inclusion in EM indices began, as a focal point for signalling QFI investment inflows. Then, I carry out the evaluation for both before and after this specific point to examine how the entry of QFI has influenced herding behaviour in the SSM.

Types of Herding Based on Fundamental and Non-Fundamental Information

Now, in this section, I will explain how this paper intends to analyze the distinction between informational (spurious) and non-informational (intentional) herding within the SSM using Galariotis et al. (2015)'s approach. As highlighted in the introduction, spurious herding may be perceived as investors' response to changes in fundamental information[9] while intentional herding occurs when investors intentionally mimic each other's actions. To differentiate between these two forms of herding, Galariotis et al. (2015) break down the $CSAD_t$ measure into deviations resulting from common fundamental and non-fundamental factors. The authors hypothesized that the return factors, as specified in Fama and French (1995, 1996) and Carhart (1997), comprehensively incorporate important fundamental information that could impact investor decisions at a market-wide level[10]. Subsequently, they conducted an estimation of the regression model detailed in equation (3.8).

$$CSAD_t = \beta_0 + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \epsilon_t \tag{3.8}$$

where,

- $(R_{m,t} - R_{f,t})$ = Risk premium factor given by the excess return on the market portfolio.
- HML_t = Value premium factor given by high book-to-market value returns minus low book-to-market value returns.

[9] Bikhchandani and Sharma (2000) initially characterized this phenomenon as "spurious herding," suggesting that investors may reach similar decisions due to their reaction to the same changes in fundamental information.

[10] It is worth mentioning that research in the field has demonstrated that the multi-factor model proposed by Fama and French (1995, 1996), along with Carhart (1997)'s momentum factor, have been shown to effectively capture fundamental information. For example, Liew and Vassalou (2000) discovered that HML and SMB factors provide valuable insights into predicting future Gross Domestic Product (GDP) growth in the US as well as nine international markets. Gregory et al. (2003) documented a positive relationship between HML and future GDP growth in the UK market. Similarly, Kessler and Scherer (2010) established a strong connection between momentum and macroeconomic indicators.

- SMB_t = Size premium factor given by small cap returns minus large cap returns.
- MOM_t = Momentum factor introduced by Carhart (1997).

In their study, Galariotis et al. (2015) view the residual (ϵ_t) in the model as the cross-sectional absolute deviations excluding the impact of fundamental information ($CSAD_{NONFUND,t}$) given that both $CSAD_t$ and the return factors are being expressed in the return form. This suggests that return dispersion resulting from fundamental information can be computed as specified in equation (3.9).

$$CSAD_{FUND,t} = CSAD_t - CSAD_{NONFUND,t} \tag{3.9}$$

$CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ represent the cross-sectional absolute deviations resulting from fundamental and non-fundamental information, respectively. According to Galariotis et al. (2015), this method can be utilized to detect return deviations attributed to non-fundamental information and employ them as a proxy for intentional herding behaviour. Similarly, this method enables us to recognize return deviations resulting from fundamental information and utilize them as a proxy for spurious herding. Therefore, two regression models like in the equation (3.5) will be estimated, but with each of the $CSAD$ measures derived from equations (3.8) and (3.9). These two models are described in equations (3.10) and (3.11).

$$CSAD_{FUND,t} = \alpha + \gamma_1 |R_{p,t}| + \gamma_2 R^2_{p,t} + \epsilon_t \tag{3.10}$$

$$CSAD_{NONFUND,t} = \alpha + \gamma_1 |R_{p,t}| + \gamma_2 R^2_{p,t} + \epsilon_t \tag{3.11}$$

In order to compute the Fama and French three factors along with Carhart's momentum factor, the study employs the method of forming six value-weighted portfolios formed on size and book-to-market on its three sets of investment portfolios (Overall, QFI, and Local), following the guidelines provided in Professor French's data library[11]. Once the factors are constructed for each of the three main investment portfolios[12], this paper conducts an estimation of the two regression models specified in equations (3.10) and (3.11) for the three constructed investment portfolios over two time periods (prior to and following the SSM's inclusion in the EM indices) to examine the nature of herding seen in the SSM before and

[11] The method of constructing the return factors is detailed on the following website $https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/$

[12] Given that the three investment portfolios have been constructed for our core analysis, three distinct sets of return factors have been generated to represent each of the investment portfolios.

after QFI entry. This approach aims to determine whether the presence of QFI has impacted trading patterns in the SSM, leading to a transition from one form of herding behaviour to another. The hypothesis is rooted in the belief that QFI investments are overseen by experienced professionals who base their choices on market data and are less inclined to engage in intentional herding behaviour due to a potential lack of familiarity with the Arabic language (the market's most common language).

3.3.2 Data Collection

Due to the sensitive nature and privacy considerations involved in accessing individuals' investment data, such as investor type and his/her nationality, this empirical study relies on publicly accessible financial information. Daily stock price data for all listed stocks on the SSM from August 31, 2014 to January 25, 2024 has been obtained from the Saudi Stock Exchange website. By the end of the sample period, a total of 251 companies were listed in the SSM. Out of these, 120 stocks are constituents of the MSCI Saudi Arabia Investable Market Index (IMI), representing 99% of Saudi's investment opportunities available for QFIs. The list of the 120 stocks included in the MSCI IMI was obtained from MSCI's website. In order to mitigate sampling bias, this study omitted approximately 58 stocks from consideration as they were listed in the SSM after 2019. This leaves a focus on the remaining 193 stocks, with 86 of them included in the MSCI IMI and 107 exclusive to local investors. As previously stated in the methodology section, this study formed three market portfolios (sample sets). The first portfolio comprises all 193 listed stocks in the SSM. The second portfolio consists of the 86 stocks available for investment by QFIs. Lastly, the third includes the remaining stocks exclusive to local investors.

The raw data required for the second part of the empirical investigation, aiming to distinguish between the types of herding observed in the three constructed investment portfolios, is also collected from the Saudi Stock Exchange website[13]. This includes daily stock price, total shares outstanding, book value, and market capitalization. This primary data is used to build three core factors (HML_t, SMB_t, and MOM_t) from the four core factor model as proposed by Fama and French (1995, 1996) and Carhart (1997). Following the guidelines provided in Professor French's website, this study created these factors using the six value-weight portfolios based on size and book-to-market as instructed on the website. For the remaining factor, the excess return on the market ($R_{mt} - R_{ft}$), this paper computes it by utilizing the daily SSM general index (TASI) returns for market return (R_{mt}) and the daily

[13] To be more precise, data were collected from the Daily Financial Indicator Reports published in the Saudi Stock Exchange website.

US treasury real long-term rates for risk-free rates (R_{ft})[14]. The choice of risk-free rates was made due to a lack of available index representing risk-free rates in the relatively new Saudi Debt market; additionally, considering that Saudi Arabia's currency is closely tied to the value of the US dollar, as its monetary policy follows a fixed-exchange regime with the US dollar.

3.4 Empirical Findings and Discussion

3.4.1 Summary Statistics

This section presents and discusses the descriptive statistics related to the study's main variables, the return dispersion measured by $CSAD_t$ and the portfolios' equally weighted returns $(R_{p,t})$. Table 3.1 presents a comprehensive summary of the statistical characteristics of portfolio returns $(R_{p,t})$ and the cross-sectional absolute deviation of returns $(CSAD_t)$ for the three generated investment portfolios over different time-periods. The data is segmented into three distinct time frames: the full sample period, a period from 01/09/2014 to 31/12/2018, representing the time-period before the SSM inclusion in the EM global indices, and a more recent period from 01/01/2019 to 25/01/2024, representing the time-period after the SSM inclusion. Each segment provides key statistics, including the mean, standard deviation, maximum, and minimum values of returns, as well as the results of the Dickey-Fuller and Phillips-Perron unit root tests.

For the overall investment portfolio, the full sample period consists of 2,348 observations (trading days). The mean return $(R_{p,t})$ is slightly negative at -0.018%, with a standard deviation of 1.237%, indicating moderate volatility. The maximum return recorded was 8.207% on 18/12/2014, while the minimum was -8.782% on 16/12/2014. Both the Dickey-Fuller and Phillips-Perron tests strongly reject the null hypothesis at the 1% significance level, suggesting that the return series is stationary at their level. The $CSAD_t$ for the same period has a mean of 1.138% and a standard deviation of 0.382%, with the highest dispersion observed on 07/11/2017 at 3.830% and the lowest on 20/09/2017 at 0.542%. The unit root tests for $CSAD_t$ also indicate stationary at a 1% significance level.

During the period prior to the SSM inclusion (from 01/09/2014 to 31/12/2018), which includes 1,081 observations (trading days), the overall investment portfolio shows also a negative mean return of -0.072% but with an increased standard deviation of 1.441%, reflecting higher return volatility compared with the full sample period. The maximum and minimum

[14] Retrieved from: The US Treasury Department - Interest Rate Statistics $https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics/legacy-interest-rate-xml-and-xsd-files.$

returns are consistent with the full sample period, given they were observed during this sub-period. The $CSAD_t$ mean is slightly higher at 1.153%, with a standard deviation of 0.449%. Both unit root tests confirm the stationarity of the series during this period at 1% level.

In the more recent period after the SSM inclusion (from 01/01/2019 to 25/01/2024), the overall portfolio demonstrates a positive shift with a mean return of 0.028% and a reduced standard deviation of 1.030%, suggesting lower volatility compared with the previous two time-periods. The maximum return is 6.325%, observed on 10/03/2020, and the minimum is -8.662%, seen on 03/05/2020. The $CSAD_t$ mean is 1.126%, with a standard deviation of 0.315%, indicating a lower dispersion in returns. The unit root tests for this period reaffirm the stationarity of both the portfolio return and its dispersion series at a 1% significance level.

The portfolio with QFI investments, over the full sample period, presents a mean return of -0.002% with a standard deviation of 1.143%. The maximum return recorded is 8.131% on 18/12/2014, and the minimum is -8.50% on 08/03/2020. The $CSAD_t$ for this period has a mean of 1.074% and a standard deviation of 0.336%, with the highest dispersion on 25/10/2020 at 3.157% and the lowest on 02/06/2015 at 0.446%. Both unit root tests indicate that both series are stationary at 1% level.

Before the SSM inclusion, the portfolio with QFI investments shows a mean return of -0.055% and a standard deviation of 1.306%, with the highest return being 8.131% on 18/12/2014 and the lowest -8.255% on 16/12/2014. The $CSAD_t$ mean is 1.060%, with a standard deviation of 0.388%. The unit root tests for both series confirm their stationarity.

In the period after the inclusion, the portfolio with QFI investments reports a mean return of 0.044% and a reduced standard deviation of 0.980%. The highest return during this period is 6.453% on 10/03/2020, while the lowest is -8.50% on 08/03/2020. The $CSAD_t$ mean is 1.086%, with a standard deviation of 0.284%. The unit root tests continue to indicate stationarity for both series.

The domestic investment portfolio's full sample period statistics reveal a mean return of -0.032% and a standard deviation of 1.360%. The maximum return is 8.159% on 16/12/2014, with the minimum being -9.143% on the same date. The $CSAD_t$ mean is 1.168%, with a standard deviation of 0.439%. The highest dispersion is 3.821% on 14/02/2016, and the lowest is 0.509% on 20/09/2017. The unit root tests for this period confirm the stationarity of both series.

During the period prior the inclusion, the domestic portfolio shows a mean return of -0.085% and a higher standard deviation of 1.590%. The maximum and minimum returns are consistent with the full sample period. The $CSAD_t$ mean is 1.206%, with a standard deviation of 0.489%. The unit root tests confirm the stationarity of both series during this time-period.

In the period post the inclusion, the domestic portfolio demonstrates a positive mean return of 0.014% with a standard deviation of 1.125%. The maximum return recorded is 6.190% on 10/03/2020, and the minimum is -8.827% on 03/05/2020. The $CSAD_t$ mean is 1.136%, with a standard deviation of 0.390%. The unit root tests confirm that both the portfolio return and its dispersion series remain stationary.

Across all three constructed investment portfolios and time periods, the mean returns are generally low and sometimes negative, indicating marginal returns. Volatility, as measured by standard deviation, varies across periods, with the highest volatility observed during the earlier period prior to the SSM inclusion in global EM indices (01/09/2014 - 31/12/2018). The $CSAD_t$ values reflect moderate dispersion in returns, with peaks occurring during specific dates. The unit root tests for returns and $CSAD_t$ consistently reject the null hypothesis at the 1% level, indicating that the series is stationary throughout the periods analyzed.

Table 3.1: Descriptive Statistics of $R_{p,t}$ (Portfolio Returns) and $CSAD_t$ for the Three Generated Investment Portfolios

Portfolio/variables	Sample period (obs.)	Mean (%)	S.D. (%)	Maximum (%) (Date)	Minimum (%) (Date)	Dickey–Fuller test	Phillips–Perron test
Overall Investment Portfolio							
$R_{p,t}$	Full sample period (2,348)	-0.01806	1.236974	-8.781711 (16/12/2014)	8.206654 (18/12/2014)	-45.244***	-45.421***
$CSAD_t$	Full sample period (2,348)	1.138193	0.38243	0.541714 (20/09/2017)	3.830198 (07/11/2017)	-22.535***	-22.388***
$R_{p,t}$	01/09/2014 - 31/12/2018 (1,081)	-0.07191	1.441063	-8.781711 (16/12/2014)	8.206654 (18/12/2014)	-29.517***	-29.585***
$CSAD_t$	01/09/2014 - 31/12/2018 (1,081)	1.152937	0.448653	0.541714 (20/09/2017)	3.830198 (07/11/2017)	-15.377***	-15.207***
$R_{p,t}$	01/01/2019 - 25/01/2024 (1,267)	0.02789	1.029789	-8.662971 (03/05/2020)	6.325471 (10/03/2020)	-35.790***	-36.355***
$CSAD_t$	01/01/2019 - 25/01/2024 (1,267)	1.125613	0.314761	0.562729 (04/07/2019)	3.298713 (06/12/2020)	-16.502***	-16.323***
Portfolio with QFI Investments							
$R_{p,t}$	Full sample period (2,348)	-0.00152	1.14253	-8.5 (08/03/2020)	8.13093 (18/12/2014)	-45.347***	-45.463***
$CSAD_t$	Full sample period (2,348)	1.073964	0.335926	0.4457899 (02/06/2015)	3.15681 (25/10/2020)	-23.2***	-23.3***
$R_{p,t}$	01/09/2014 - 31/12/2018 (1,081)	-0.05489	1.305811	-8.255301 (16/12/2014)	8.13093 (18/12/2014)	-29.802***	-29.814***
$CSAD_t$	01/09/2014 - 31/12/2018 (1,081)	1.059907	0.388034	0.4457899 (02/06/2015)	2.992054 (14/02/2016)	-15.804***	-15.820***
$R_{p,t}$	01/01/2019 - 25/01/2024 (1,267)	0.04401	0.980238	-8.5 (08/03/2020)	6.452917 (10/03/2020)	-35.19***	-35.824***
$CSAD_t$	01/01/2019 - 25/01/2024 (1,267)	1.085956	0.283622	0.4991386 (04/07/2019)	3.15681 (25/10/2020)	-17.056***	-16.926***
Portfolio of Domestic Investments							
$R_{p,t}$	Full sample period (2,348)	-0.03187	1.359544	-9.143266 (16/12/2014)	8.159081 (16/12/2014)	-44.75***	-44.951***
$CSAD_t$	Full sample period (2,348)	1.168385	0.439416	0.508606 (20/09/2017)	3.821393 (14/02/2016)	-22.142***	-22.013***
$R_{p,t}$	01/09/2014 - 31/12/2018 (1,081)	-0.08547	1.590195	-9.143266 (16/12/2014)	8.159081 (16/12/2014)	-29.168***	-29.272***
$CSAD_t$	01/09/2014 - 31/12/2018 (1,081)	1.205782	0.488552	0.508606 (20/09/2017)	3.821393 (14/02/2016)	-15.112***	-14.942***
$R_{p,t}$	01/01/2019 - 25/01/2024 (1,267)	0.013866	1.124664	-8.827094 (03/05/2020)	6.190444 (10/03/2020)	-35.470***	-35.840***
$CSAD_t$	01/01/2019 - 25/01/2024 (1,267)	1.136478	0.390036	0.549375 (27/02/2019)	3.742373 (06/12/2020)	-16.317***	-16.051***

Notes. This table presents the daily mean, standard deviation, maximum and minimum values of returns ($R_{p,t}$), along with the cross-sectional absolute deviation of returns ($CSAD_t$) for the three constructed investment portfolios over the sample period. It also reports the test statistics from unit root tests. *** denotes rejection of the null hypothesis at the 1% significance level.

3.4.2 Regression Results

In this section, this paper will present and analyze the primary results obtained from our empirical specifications related to the overall return dispersion approach and the utilized model to differentiate between intentional and spurious herding. In the first sub-section, our analysis will concentrate on identifying herding behaviour in the SSM at a market-wide scale. This will involve examining the behaviour observed in our three investment portfolios throughout the sample period, before and after the SSM inclusion in the global EM indices. The focus of the investigation in the second sub-section will turn to analyzing the type of herding present in the three portfolios constructed and across the various time periods.

Return Dispersion Approach to Detect Herding at the Market-wide Level

Table 3.2 shows the results of the empirical specifications in equations (3.5), (3.6) and (3.7) estimated individually for each of the three constructed portfolios across entire, positive, and negative market conditions over the complete period from 01/09/2014 to 25/01/2024. The magnitude of the equally weighted absolute return is utilized to compare the linear term's coefficients in different market conditions for each portfolio. The quadratic component of the equally weighted return is employed to identify the presence of herding behaviour in the underlying stocks of each portfolio. As per Chang et al. (2000), a negative and statistically significant parameter γ_2 signals the presence of herding behaviour in the model of estimation. The Wald test statistic with $\chi^2(1)$ distribution is also utilized to assess, under the null hypothesis, whether γ_1^D equals γ_1^U or if γ_2^D equals γ_2^U to investigate if investors behave differently given the market directions.

The regression findings reveal that the average levels of equity return dispersion, measured by the regression coefficient α, in a stagnant market where $R_{p,t}$ equals zero, vary from high points of 0.875%, 0.857%, and 0.888% for the overall portfolio to low points of 0.844%, 0.813%, and 0.860% for the domestic investment portfolio in whole, declining, and rising market conditions, respectively. Additionally, I observe that all coefficients (γ_1) on the linear term of $|R_{p,t}|$ are both statistically significant and positive. These results strongly support the hypothesis that $CSAD_t$ increases with $|R_{p,t}|$. However, in most cases, particularly in the up market conditions, the parameter estimates for the non-linear term in all constructed portfolios show evidence of herding behaviour. This is evident from the negative and statistically significant γ_2 coefficients. This indicates that the linear correlation between $CSAD_t$ and $|R_{p,t}|$ does not hold under most market conditions. It suggests that as the average equally weighted return on constructed portfolios increases significantly, the cross-sectional return dispersion increases at a decreasing pace. The estimated coefficients suggest that once a certain threshold is exceeded, the $CSAD_t$ may decrease as $|R_{p,t}|$ grows larger. The tendency is for it to become narrower once the portfolio return surpasses the threshold, typically during significant market movements[15]. This aligns with Christie and Huang (1995)'s intuition that individuals tend to withhold their own beliefs and follow the market consensus during times of extreme market movements.

The Wald test statistics with $\chi^2(1)$ distribution for γ_1 and γ_2 indicate no significant difference between up and down market conditions, suggesting similar herding behaviour in both market directions for the overall investment portfolio as well as the portfolio with QFI investments. Nonetheless, The Wald test statistics with $\chi^2(1)$ distribution for γ_2 in the regression model estimated for the portfolio of domestic investments shows a significant difference between up and down market conditions, indicating that local investors' herding behaviour varies with market direction, potentially being more pronounced in one direction than the other.

[15] The $CSAD_t$ reaches its maximum value (threshold level) when $[R^{'}_{p,t} = -(\gamma_1/(2 \cdot \gamma_2))]$ derived from the general quadratic relationship specified in the form of $CSAD_t = \alpha + \gamma_1 R_{p,t} + \gamma_2 R^2_{p,t}$. For instance, when we substitute the estimated domestic portfolio coefficients for the up market direction (γ_1 = 0.425 and γ_2 = -0.027) into the previously mentioned equation, we find that $CSAD_t$ achieves its maximum value at $R_{p,t} = 7.87\%$.

Table 3.2: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over Full Sample Period for Whole, Up, and Down Market Conditions

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.875***	0.362***	-0.010***	0.616	0.857***	0.390***	-0.012**	0.716	0.888***	0.351***	-0.019***	0.427	2,348	1.8	1.31
	(104.05)	(22.40)	(-2.68)		(68.42)	(16.65)	(-2.56)		(88.26)	(20.12)	(-6.25)				
Portfolio with QFI Investments	0.867***	0.295***	-0.007*	0.479	0.850***	0.311***	-0.007	0.590	0.881***	0.287***	-0.010***	0.328	2,348	0.64	0.26
	(99.94)	(18.73)	(-1.87)		(67.52)	(13.83)	(-1.60)		(76.27)	(14.34)	(-2.57)				
Portfolio of Domestic Investments	0.844***	0.416***	-0.016***	0.636	0.813***	0.435***	-0.017***	0.741	0.860***	0.425***	-0.027***	0.459	2,348	0.13	4.08**
	(92.51)	(27.87)	(-5.41)		(62.14)	(20.13)	(-4.51)		(71.25)	(23.21)	(-7.71)				

Notes. The table displays the calculated coefficients of the regression models specified in (3.5), (3.6) and (3.7), offering a comprehensive overview of the correlation between the Daily $CSAD_t$ and $R_{p,t}$. The data covers the entire sample period from 01/09/2014 to 25/01/2024. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. The Wald test statistic is utilized to test the Null hypothesis that either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$ from models (3.6) and (3.7). *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively.

To evaluate the influence of QFI entry on the existing herding behaviour in the SSM, I segmented the entire sample duration into two parts by recognizing the beginning of 2019 as a significant point when QFI investment inflows started due to the SSM inclusion in the global EM indices. Then, the empirical specifications in equations (3.5), (3.6), and (3.7) are estimated separately for each of the three formed portfolios during overall, positive, and negative market conditions over both time frames from 01/09/2014 to 31/12/2018 and from 01/01/2019 to 25/01/2024. Table 3.3 shows the results of the estimations for the period before the SSM inclusion from 01/09/2014 to 31/12/2018, while Table 3.4 displays the results of the estimations for the period after the SSM inclusion from 01/01/2019 to 25/01/2024.

The regression results from Table 3.3 indicate that the mean levels of equity return dispersion, represented by the regression coefficients α, vary in a stagnant market scenario where $R_{p,t}$ is zero. The values range from highs of 0.847% and 0.869% for the domestic investment portfolio to lows of 0.782% and 0.784% for the portfolio with QFI investments[16] in both the whole and upward market conditions, respectively. In a bearish (downward) market context, the average levels of return dispersion range from a peak of 0.819% for the overall investment portfolio to a trough of 0.779% for the middle portfolio within Table 3.3. Regarding herding behaviour presence, strong indications are observed in the non-linearity parameter estimates γ_2 showing a presence of herding behaviour in all the three portfolios during both whole and rising market conditions. However, no sign of herding behaviour is observed in neither the first portfolio nor the middle portfolio within Table 3.3 during declining markets covering time period between 01/09/2014 to 31/12/2018. The Wald test statistics for γ_2 support this finding by indicating an increased tendency towards herding behaviour evident only during bullish market conditions as identified within first two listed portfolios on our table.

As for the period after the SSM inclusion in the global EM indices, the results of the regression analysis presented in Table 3.4 indicate that the mean levels of return dispersion, represented by the regression coefficients α, vary in a stable market where $R_{p,t}$ equals zero. The values range from highs of 0.936%, 0.919%, and 0.956% for the portfolio with QFI investments to lows of 0.834%, 0.810%, and 0.836% for the domestic investment portfolio in the overall, bearish, and bullish market conditions, respectively. Regarding herding behaviour presence, notable evidence is found in the non-linearity parameter estimates γ_2, highlighting a

[16] During this time-frame (01/09/2014 - 31/12/2018), the underlying stocks in this portfolio are only being traded by local investors. Qualified Foreign Investors (QFI) have not yet participated in the trading activity of the SSM. I maintained the name for consistency with the rest of the analysis.

strong presence of herding behaviour across both the overall and domestic portfolios during all market conditions. However, the results show no sign of herding behaviour within the portfolio with QFI investments in the whole or upward market conditions; it was only observable during the downward market conditions with a 5% significant level. This is supported by the findings of the Wald test statistics for γ_1 and γ_2. The results of the Wald test statistics for γ_1 seen in the overall portfolio and the portfolio with the QFI investments suggesting significant differences between the two Market conditions, which indicate different behaviour intensities. This is consistent with the presence of foreign investors who might respond differently to Market conditions than local investors thereby influencing the dynamics post-inclusion. In fact, the presence of significant herding behaviour in down markets for the portfolio with QFI investments highlights the cautious behaviour of foreign investors during market downturns. Importantly, the absence of herding in overall and bullish market conditions suggests that QFIs, assuming their reliance on fundamentals, do not follow the same sentiment-driven patterns as domestic retail investors. This behavioural distinction provides valuable insight into how QFIs maintain their investment discipline in the SSM, in contrast to the stronger herding tendencies of local retail investors. This insight becomes even more relevant when considering possible contributing factors: language barriers that may limit QFIs' use of local media and social platforms, the dominance of retail investors in the Saudi market (often accounting for 70–80% of trading activity), the fact that the Saudi market represents only a small fraction of QFIs' global investment portfolios, and the widespread use of algorithmic and systematic trading strategies among QFIs, which are specifically designed to reduce behavioural biases and mitigate herd-like behaviour. Together, these factors help explain why QFIs do not herd in the same way as local participants and why their behaviour post-inclusion is analytically significant. This contrast makes clear that QFIs and local retail investors behave in fundamentally different ways, and each group plays a distinct role in shaping market dynamics after the inclusion. Moreover, the significant Wald test statistic for γ_2 seen in the domestic portfolio suggests different herding intensities in the up and down markets. This increase in herding behaviour post-inclusion may indicate that local investors are reacting more strongly to market movements, possibly because the presence of foreign investors drew more attention to the market and increased trading activity, which local investors may have interpreted as a signal to follow, thereby intensifying their herding behaviour.

Table 3.3: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period Before the SSM Inclusion for Whole, Up, and Down Market Conditions

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.828*** (69.48)	0.378*** (17.88)	-0.008* (-1.68)	0.712	0.819*** (47.92)	0.384*** (12.93)	-0.006 (-1.07)	0.800	0.832*** (54.50)	0.394*** (15.98)	-0.022*** (-5.68)	0.528	1,081	0.06	5.18**
Portfolio with QFI Investments$_{(1)}$	0.782*** (63.78)	0.353*** (16.71)	-0.010** (-2.29)	0.613	0.779*** (46.64)	0.336*** (11.57)	-0.005 (-0.89)	0.707	0.784*** (46.15)	0.378*** (14.40)	-0.021*** (-4.73)	0.481	1,081	1.15	4.91**
Portfolio of Domestic Investments	0.847*** (63.51)	0.385*** (20.55)	-0.009*** (-2.71)	0.710	0.812*** (45.04)	0.409*** (15.44)	-0.011** (-2.52)	0.812	0.869*** (46.07)	0.389*** (15.97)	-0.020*** (-4.37)	0.495	1,081	0.31	1.97

Notes. The table displays the estimated coefficients of the regression models specified in (3.5), (3.6) and (3.7), offering a comprehensive overview of the correlation between the Daily CSAD and Portfolio Returns. The data covers the sample period before the SSM inclusion in the EM indices, spanning from 01/09/2014 to 31/12/2018. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. The Wald test statistic is utilized to test the Null hypothesis that either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$ from models (3.6) and (3.7). *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively. (1) Please note that this period does not include QFI investments since their inflows started after the inclusion in the EM indices, which took place in the year 2019. The underlying 86 stocks of this portfolio are only traded by local investors during this period (from 01/09/2014 to 31/12/2018).

Table 3.4: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period After the SSM Inclusion for Whole, Up, and Down Market Conditions

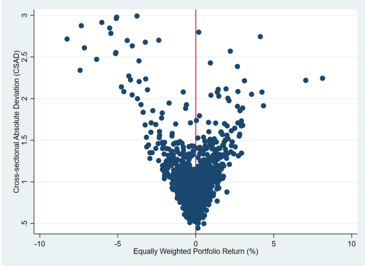
Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.910***	0.354***	-0.017***	0.483	0.893***	0.393***	-0.021***	0.594	0.926***	0.323***	-0.021***	0.317	1,267	3.33*	0.00
	(84.31)	(17.04)	(-3.96)		(55.56)	(13.27)	(-4.12)		(69.74)	(13.08)	(-4.55)				
Portfolio with QFI Investments	0.936***	0.242***	-0.005	0.332	0.919***	0.280***	-0.010**	0.455	0.956***	0.200***	-0.0004	0.184	1,267	4.21**	2.05
	(83.52)	(11.71)	(-1.22)		(55.87)	(9.86)	(-2.01)		(64.27)	(7.47)	(-0.08)				
Portfolio of Domestic Investments	0.834***	0.461***	-0.028***	0.542	0.810***	0.470***	-0.027***	0.634	0.836***	0.501***	-0.048***	0.429	1,267	0.51	7.81***
	(68.09)	(21.54)	(-7.32)		(44.45)	(14.97)	(-5.54)		(50.80)	(16.70)	(-8.42)				

Notes. The table displays the estimated coefficients of the regression models specified in (3.5), (3.6) and (3.7), offering a comprehensive overview of the correlation between the Daily CSAD and Portfolio Returns. The data covers the sample period after the SSM inclusion in the EM indices, spanning from 01/01/2019 to 25/01/2024. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. The Wald test statistic is utilized to test the Null hypothesis that either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$ from models (3.6) and (3.7). *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively.

To demonstrate the extent of the non-linear relationship between $CSAD_t$ and $R_{p,t}$ represented by the γ_2 coefficients before and after the inclusion of SSM in global EM indices, Figures 3.3 and 3.4 plot the $CSAD_t$ measure for each day against the equally weighted portfolio return ($R_{p,t}$). These visualizations cover all the three portfolios analyzed during two periods: prior to inclusion from 01/09/2014 to 31/12/2018 and post-inclusion from 01/01/2019 to 25/01/2024. When Looking at Figure 3.4b, it is evident that there exists an unclear non-linear relationship between $CSAD_t$ and $R_{p,t}$ for the portfolio with QFI investments, following the SSM inclusion. This finding aligns with the regression results in Table 3.4, indicating no significant herding behaviour for this portfolio's underlying stocks. Nevertheless, plots of both sub-periods within the overall investment portfolio and the domestic portfolio, along with the portfolio with QFI investments for the period before the inclusion, reveal a clear non-linear association between $CSAD_t$ and $R_{p,t}$. This highlights strong evidence of herding behaviour as confirmed by Figures 3.3a, 3.3c, 3.4a, and 3.4c; supported by regression analysis from Tables 3.3 and 3.4. Furthermore, it is possible to visualize the slightly steeper slopes in the upward market compared to the downward market for the portfolios, where herding behaviour is strongly evident. Upon examining Figures 3.3b and 3.4b, which displays the scatter plot of the portfolio with QFI investments, it is apparent that there is a noticeable decrease in the growth of cross-sectional return dispersion as the average equally weighted portfolio return increases during the period prior the SSM's inclusion. Nonetheless, this pattern appears to weaken following the inclusion, indicating that the non-linear association between $CSAD_t$ and $R_{p,t}$ becomes less apparent. The regression estimate of γ_2, however, is negative (though insignificant), which does not match the positive benchmark for no herding and thus offers only weak, inconclusive evidence in the direction of herding behaviour.

Beyond market-portfolio level investigations, it is also important to consider whether herding behaviour in the SSM varies with firm characteristics. Firm size, in particular, plays a critical role in shaping investor herding behaviour. Larger firms are typically more liquid and better covered by financial analysts while smaller firms may be more prone to information asymmetries and noise trading (Lakonishok et al., 1992; Choi and Sias, 2009). To investigate this dimension, an additional analysis is conducted to assess whether the size of listed companies influences the extent of herding behaviour observed in the SSM. By running the regression analysis across the three market portfolios and over the periods before and after the SSM's inclusion, separately for two stock size groups (large-cap listed companies versus small- and medium-cap listed companies), we find that firm size does influence herding behaviour in the SSM (See Tables B.2, B.3, B.4, B.5, B.6, and B.7 and Figures B.2, B.3, B.4,

(a) The Relationship in the Overall Investment Portfolio



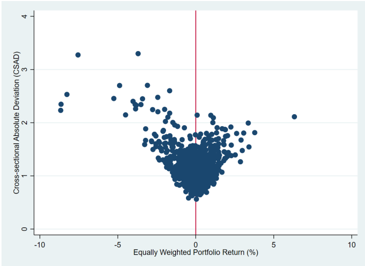
(b) The Relationship in the Portfolio with QFI Investments

(c) The Relationship in the Dedicated Portfolio for Domestic Investments

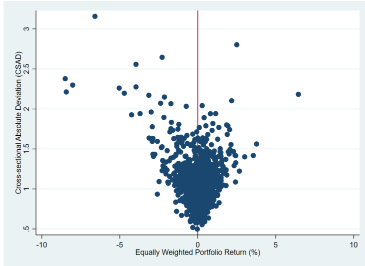
Figure 3.3: The Relationship between the Daily Cross-sectional Absolute Deviation ($CSAD_t$) and the Corresponding Equally Weighted Investment Portfolio Return ($R_{p,t}$) over the Period Before the SSM Inclusion

and B.5). Specifically, the results indicate that herding behaviour is evident both before and after the inclusion among all three large-cap market portfolios, including the large-cap portfolio with QFI investments and the large-cap portfolio of domestic investments. In contrast, herding behaviour is significantly observable in the small- and medium-cap segment only for the portfolio comprising local investments. This distinction suggests that larger firms, with greater liquidity and broader information availability and coverage, encourage more consistent herding across both foreign and domestic investors whereas herding in smaller firms appears more localized driven primarily by domestic participants facing higher information asymmetry.

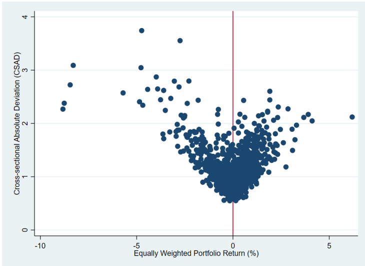
Overall, The regression results and visual analysis indicate consistent herding behaviour in the SSM, characterized by negative and significant γ_2 coefficients. This behaviour persists before and after the market's inclusion in the EM global indices, though the intensity varies across different market conditions and portfolios. The Wald test statistics reveal significant differences in herding behaviour between up and down market conditions, particularly in the post-inclusion period, suggesting that market inclusion in the global EM indices may influence herding dynamics. The distinct behaviours observed in the portfolios with QFI investments and domestic investments highlight the differing impacts of foreign and local investor trading activities on market dynamics. This analysis emphasizes the importance of monitoring herding behaviour to maintain financial market stability and efficiency, especially in the context of



(a) The Relationship in the Overall Investment Portfolio



(b) The Relationship in the Portfolio with QFI Investments



(c) The Relationship in the Dedicated Portfolio for Domestic Investments

Figure 3.4: The Relationship between the Daily Cross-sectional Absolute Deviation ($CSAD_t$) and the Corresponding Equally Weighted Investment Portfolio Return ($R_{p,t}$) over the Period After the SSM Inclusion

increased foreign participation in the market.

Testing for Type of Herding with Fundamental and Non-fundamental Information

After conducting the regression model indicated in equation (3.8), this research uses the determined standard error (ϵ_t) extracted from the model as a crucial element in analyzing the dispersion of returns resulting from non-fundamental information ($CSAD_{NONFUND,t}$). Subsequently, the return dispersion driven by fundamental factors ($CSAD_{FUND,t}$) is computed by subtracting the non-fundamentally driven $CSAD_t$ from the total $CSAD_t$ (Refer to equation (3.9)). Once both $CSAD_{NONFUND,t}$ and $CSAD_{FUND,t}$ are calculated, regression models specified in equations (3.10) and (3.11) are estimated for the periods before and after the SSM's inclusion in global EM indices. The results of empirical specifications for the period before inclusion can be found in Table 3.5, while those related to the period after inclusion are presented in Table 3.6. Moreover, Figures 3.5 and 3.6 illustrate the non-linear relationship between fundamentally driven $CSAD_t$ and non-fundamentally driven $CSAD_t$ with the corresponding equally weighted portfolio return ($R_{p,t}$). These visualizations encompass both the portfolio with QFI investments and the one with only domestic investments analyzed during two periods: before inclusion from 01/09/2014 to 31/12/2018, and after inclusion from 01/01/2019 to 25/01/2024.

The regression findings from Table 3.5 suggest that the herding behaviour observed before the inclusion of SSM in EM indices cannot be explained by fundamental information. This suggests that investors trading in the SSM tend to exhibit intentional herding behaviour, particularly during up-market conditions. However, the results also show spurious herding behaviour during up-market conditions for the underlying stocks of the portfolio with QFI investments[17], with an R^2 of only 1.6%. On the other hand, according to Table 3.6's regression results for the period after the inclusion, intentional herding behaviour remains significant for the overall and domestic investment portfolios. However, herding behaviour observed in the portfolio with QFI investments becomes insignificant after SSM's inclusion in the global EM indices. Additionally, the results suggest that spurious herding behaviour is significantly observable during down markets for the overall and domestic portfolios post-inclusion, indicating that some of the herding behaviour observed during this time period can be justified using fundamental information.

[17] As mentioned before, the underlying stocks of this portfolio are only traded by local investors at this stage.

Table 3.5: Regression Results of Daily Fundamentally Driven $CSAD_t$ and Non-fundamentally Driven $CSAD_t$ on $R_{p,t}$ Over the Period Before SSM Inclusion for Whole, Up, and Down Market Conditions

Portfolio	Whole Market Conditions			Down Market Conditions			Up Market Conditions		
	γ_1	γ_2	R^2	γ_1^D	γ_2^D	R^2	γ_1^U	γ_2^U	R^2
Panel A: Fundamentally Driven $CSAD_t$									
Overall Investment Portfolio	0.021	0.014***	0.295	0.154***	-0.001	0.777	-0.086***	0.003	0.129
	(0.98)	(2.72)		(14.96)	(-0.75)		(-6.20)	(1.64)	
Portfolio with QFI Investments $(*)$	0.062***	-0.001	0.126	0.111***	-0.004	0.148	0.017	-0.007***	0.016
	(3.55)	(-0.22)		(6.27)	(-1.20)		(1.17)	(-2.86)	
Portfolio of Domestic Investments	-0.022	0.017***	0.330	0.114***	0.002*	0.831	-0.100***	0.001	0.382
	(-1.40)	(5.38)		(15.22)	(1.67)		(-8.71)	(0.18)	
Panel B: Non-fundamentally Driven $CSAD_t$									
Overall Investment Portfolio	0.357***	-0.022***	0.491	0.230***	-0.005	0.583	0.480***	-0.025***	0.554
	(16.02)	(-5.35)		(8.79)	(-1.00)		(17.83)	(-6.30)	
Portfolio with QFI Investments $(*)$	0.291***	-0.009***	0.488	0.225***	-0.001	0.551	0.361***	-0.015***	0.470
	(14.81)	(-2.82)		(8.22)	(-0.15)		(14.00)	(-3.73)	
Portfolio of Domestic Investments	0.407***	-0.027***	0.526	0.295***	-0.013***	0.616	0.488***	-0.0201***	0.554
	(18.51)	(-7.28)		(10.95)	(-2.82)		(16.71)	(-2.83)	

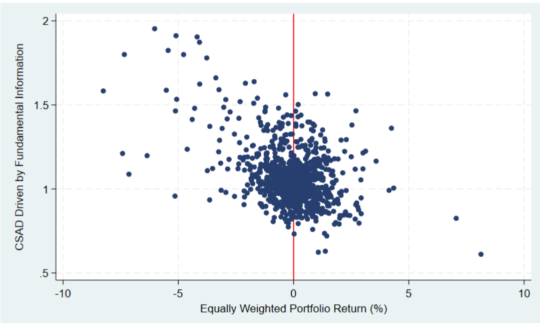
Notes. The table displays the calculated coefficients of the regression models specified in (3.10) and (3.11), offering a comprehensive overview of the correlation between the Daily $CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ with $R_{p,t}$. The daily $CSAD_{NONFUND,t} = \epsilon_t$ and is extracted from the regression model specified in equation (3.8). Then, the daily $CSAD_{FUND,t}$ is computed as specified in (3.9). The data covers the sample period before the SSM inclusion in the EM indices, spanning from 01/09/2014 to 31/12/2018. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively. $(*)$ Please note that this period does not include QFI investments since their inflows started after the inclusion in the EM indices, which took place in the year 2019. The underlying 86 stocks of this portfolio are only traded by local investors during this period (from 01/09/2014 to 31/12/2018).

Table 3.6: Regression Results of Daily Fundamentally Driven $CSAD_t$ and Non-fundamentally Driven $CSAD_t$ on $R_{p,t}$ Over the Period After SSM Inclusion for Whole, Up, and Down Market Conditions

Portfolio	Whole Market Conditions			Down Market Conditions			Up Market Conditions		
	γ_1	γ_2	R^2	γ_1^D	γ_2^D	R^2	γ_1^U	γ_2^U	R^2
Panel A: Fundamentally Driven $CSAD_t$									
Overall Investment Portfolio	0.020**	0.003**	0.061	0.077***	-0.004***	0.267	-0.030***	-0.002	0.045
	(2.19)	(2.10)		(8.36)	(-3.41)		(-2.62)	(-0.78)	
Portfolio with QFI Investments	0.014*	-0.001	0.016	0.041***	-0.003	0.118	-0.0002	-0.007***	0.050
	(1.92)	(-0.26)		(4.85)	(-1.58)		(-0.03)	(-3.65)	
Portfolio of Domestic Investments	0.001	0.003***	0.079	0.050***	-0.003***	0.464	-0.044***	0.002	0.312
	(0.21)	(3.48)		(12.07)	(-4.34)		(-10.11)	(1.16)	
Panel B: Non-fundamentally Driven $CSAD_t$									
Overall Investment Portfolio	0.334***	-0.020***	0.434	0.316***	-0.017***	0.512	0.354***	-0.019***	0.367
	(17.26)	(-4.73)		(11.43)	(-3.43)		(13.75)	(-3.60)	
Portfolio with QFI Investments	0.229***	-0.005	0.316	0.238***	-0.006	0.415	0.200***	0.007	0.220
	(10.80)	(-0.98)		(8.32)	(-1.20)		(7.30)	(1.34)	
Portfolio of Domestic Investments	0.460***	-0.0307***	0.511	0.420***	-0.024***	0.578	0.544***	-0.050***	0.470
	(21.81)	(-9.09)		(13.42)	(-5.26)		(17.67)	(-8.22)	

Notes. The table displays the calculated coefficients of the regression models specified in (3.10) and (3.11), offering a comprehensive overview of the correlation between the Daily $CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ with $R_{p,t}$. The daily $CSAD_{NONFUND,t} = \epsilon_t$ and is extracted from the regression model specified in equation (3.8). Then, the daily $CSAD_{FUND,t}$ is computed as specified in (3.9). The data covers the sample period after the SSM inclusion in the EM indices, spanning from 01/01/2019 to 25/01/2024. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively.

Upon examining Figures 3.5 and 3.6, it can be clearly seen that the visual analysis findings are consistent with the regression results for both sub-periods before and after the SSM inclusion. In Figures 3.5b and 3.5d, it is apparent that there is a somewhat clear non-linear relationship between $CSAD_{NONFUND,t}$ and $R_{p,t}$ for the portfolio with QFI investments as well as the dedicated domestic investment portfolio during the period preceding the SSM inclusion. Nevertheless, this connection becomes weaker when considering the return deviations caused by fundamental information ($CSAD_{FUND,t}$) in relation to $R_{p,t}$ (See Figures 3.5a and 3.5c). After the inclusion of SSM, while the intentional herding behaviour continues to be notable and significant for the domestic investment portfolio (refer to Figure 3.6d), the intentional herding behaviour in the QFI investment portfolio becomes insignificant due to the unclear non-linear relationship between $CSAD_{NONFUND,t}$ and $R_{p,t}$ (See Figure 3.6b). In addition, it is possible to visualize slightly steeper slopes in the upward market compared to the downward market for portfolios that demonstrate significant intentional herding behaviour in both sub-periods. This suggests a shift in the dynamics of herding behaviour based on the market condition.



(a) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

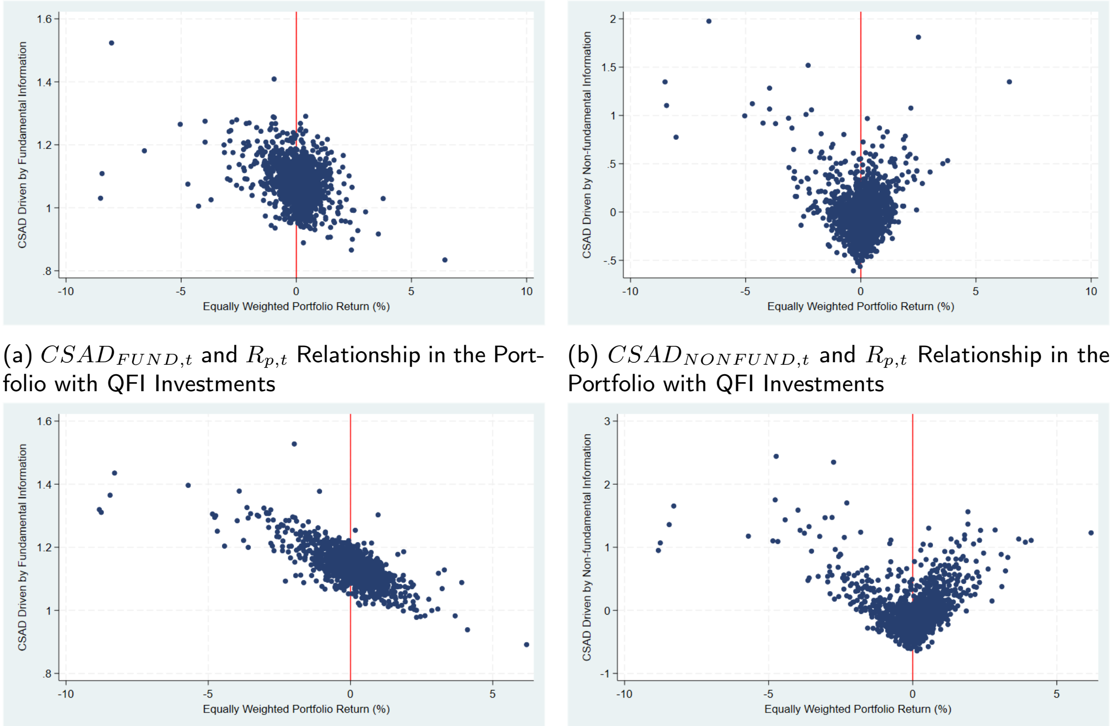
(b) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

(c) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

(d) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

Figure 3.5: The Relationship between the Daily Fundamental Driven $CSAD_t$ and Non-fundamental Driven $CSAD_t$ with the Corresponding Equally Weighted Investment Portfolio Return ($R_{p,t}$) over the Period Before the SSM Inclusion

In summary, the regression analysis and visual examination results in this section of the empirical study suggest that herding behaviour identified in the SSM can primarily be classi-



(a) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

(b) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

(c) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

(d) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

Figure 3.6: The Relationship between the Daily Fundamental Driven $CSAD_t$ and Non-fundamental Driven $CSAD_t$ with the Corresponding Equally Weighted Investment Portfolio Return ($R_{p,t}$) over the Period After the SSM Inclusion

fied as intentional herding. However, domestic investors sometimes exhibit spurious herding behaviour under various market conditions, especially during downward trends following the SSM inclusion in global EM indices. Furthermore, the findings from this section of the study indicate that intentional herding behaviour loses its significance in underlying stocks involving QFI investments after SSM inclusion but continues to be statistically significant for those with only local investor trading. These results support observations made earlier in the study, indicating that Saudi market inclusion in global EM indices may have impacted herding behaviour dynamics within varying market conditions and portfolios. This could be due to differing impacts of foreign and local investor activities on market dynamics. The analysis emphasizes monitoring herding behaviour to maintain financial market stability and efficiency, particularly given increased foreign participation in the market.

3.5 Conclusion

Investors across different financial markets are commonly thought to exhibit herding behaviour, which is seen as a significant factor contributing to periods of extreme price volatility and market instability. It is considered a leading cause of market bubbles and financial crashes, such as the 2010 European debt crisis, the Dot-com bubble, and the 2006 SSM crash. This study constructs three investment portfolios using stocks listed in the SSM pre-2019 to evaluate Tadawul's inclusion in the global EM indices and its potential impact on herding behaviour within the SSM. The first portfolio includes all the 193 listed companies before 2019. The second focuses on the 86 stocks available for QFIs while the third concentrates on the remaining exclusive stocks available for local investors (totaling 107 stocks). Estimations were conducted over three periods: overall study period from 01/09/2014 to 25/01/2024; the sub-period before Tadawul's inclusion (01/09/2014 to 31/12/2018); the sub-period after the inclusion (01/01/2019 to 25/01/2024).

This research's empirical analysis is divided into two sections. The initial section explores the existence of herding behaviour in all of the constructed portfolios and during the specified time frames using the method proposed by Christie and Huang (1995) and further developed by Chang et al. (2000) while the second section examines the nature of herding behaviour observed in the investment portfolios during the specified periods, following Galariotis et al. (2015)'s approach introduced in 2015.

The regression findings suggest consistent herding behaviour in the SSM, characterized by negative and significant γ_2 coefficients. This behaviour persists both before and after the market's inclusion in global EM indices, particularly for local investors; however, the intensity varies across different market conditions and investment portfolios. For the underlying stocks involved with QFI investments, the herding behaviour becomes insignificant during the period after the inclusion except when the market is experiencing a downward trend. This finding is supported by the Wald test statistics which indicate that the inclusion in the global EM indices may have influenced herding dynamics. Regarding investigation into herding behaviour nature, the regression analysis reveals that the identified behaviour in the SSM can mainly be classified as intentional herding behaviour. Nevertheless, domestic investors sometimes display spurious herding conduct under various market conditions, especially during the downward trends following the SSM inclusion in global EM indices. Furthermore, study results indicate that intentional herding conduct loses significance among underlying stocks involving QFI investments after the SSM inclusion but remains statistically notable for those with only local investor trades.

As for the study's limitations, the empirical research focuses on evaluating herding behaviour in the SSM and analyzing how the market inclusion in global EM indices may impact the behaviour at the macro level using market data. The challenge of assessing this impact lies in the difficulty of distinguishing QFI investments from local investments since local investors are still involved in trading the stocks, in which QFIs are trading, before and after the inclusion. To address this limitation, the study attempts to conduct estimations on the stocks not included as part of QFI investments and only accessible to local investors, as well as dividing the study time period in two time sub-periods before and after the entry of QFIs in the SSM. In terms of future studies, researchers could leverage data from diverse internet and social media channels to construct an investor attention index as an alternative that captures spurious herding behaviour. This index could then be incorporated into the study's empirical regression model, for instance, by adding dummy variables to detect shifts in investor attention. Turning these dummies on and off based on the index exceeding its median would allow investigating whether changes in investor attention amplify or diminish spurious herding within the SSM given that investors tend to seek related information during periods of market uncertainty.

Chapter 4

Quantifying Psychological Aspects of Investing Only in Shariah-compliant Stocks Using the Markowitz Regret Model: Evidence from Saudi Arabia

4.1 Introduction

> "I should have computed the historical covariance of the asset classes and drawn an efficient frontier. Instead I visualized my grief if the stock market went way up and I wasn't in it – or if it went way down and I was completely in it. My intention was to minimize my future regret, so I split my [personal pension savings] contributions 50/50 between bonds and equities."
>
> *Harry Markowitz*
> *(A Nobel Prize Winner)*

The ongoing progression of economic development presents considerable opportunities and challenges for all social and governmental entities. Capital markets across the board play crucial roles in addressing this circumstance. The investment industry has expanded significantly over the past few decades both theoretically and practically. Consequently, financial markets have become more efficiently developed, particularly in advanced economies. On a daily basis, substantial amounts of capital are directed towards diverse economic sectors by individual investors, financial intermediaries, and institutional fund managers (Arestis et al., 2001; Peykani et al., 2023). The process of building an investment portfolio involves selecting investments aiming to maximize returns by selecting the most appropriate and optimal combination of stocks from various types while considering risk management aspects. To consider both risk and return objectives in portfolio management, Markowitz (1952, 1987)'s classical portfolio optimization framework has significantly contributed to the development of most financial models employed for portfolio selection and allocation in most if not all financial markets. It is widely recognized as a cornerstone of the modern portfolio theory (MPT). This empirical optimization framework offers a structured yet feasible approach to identifying optimal portfolios. However, this feasibility is achieved at the expense of neglecting higher-order return characteristics like skewness and kurtosis, which can be important beyond just the mean and variance of returns (Baule et al., 2019). In fact, the classical Markowitz framework fails to account for factors beyond just final wealth that can be meaningful to investors, such as emotional and psychological aspects. It is essential to emphasize the selection of stocks that seek to minimize the risk of missed opportunities or regrets while also addressing the traditional trade-off between the portfolio's expected return and its volatility risk. Consequently, investors who exhibit loss or regret aversion may not be fully satisfied with the classical Markowitz framework, as it does not adequately capture their risk preferences.

Regret is conceptualized as the emotional experience arising from the ex-post awareness that an alternative decision, rather than the one actually made, would have resulted in a more favourable outcome (Loomes and Sugden, 1982; Bell, 1982, 1983). Regret aversion, a well-established phenomenon in behavioural finance and economics, reflects an investor's fear of missing out. Recent advancements have integrated this behavioural bias into the mean-variance portfolio optimization framework for portfolio management. This development stemmed from a recent study by Baule et al. (2019) that aimed to integrate the concepts of regret aversion and fear of missing out into the market-efficient portfolio frontier model. Baule et al. (2019)'s paper proposes a straightforward yet informative alteration to the covariance matrix computation within the Markowitz mean-variance framework. This empirical framework offers a distinguished mathematical model for quantifying regret in the context of portfolio selection and asset allocation decisions. Building upon this foundation, our study explores the financial and psychological opportunity costs investors may face when limiting their investment universe to Shariah-compliant assets, aiming to unravel the complex interplay between behavioural biases, the normative principles of Islamic finance, and quantitative portfolio optimization using a sample of daily stock market data of two time periods 2018 and 2023. In doing so, it seeks to provide a framework that supports investment decisions which are both financially sound and ethically aligned with investors' religious values. Therefore, the fundamental research question this study aims to address is: *To what extent does the integration of regret aversion into the portfolio optimization process impact the investment decisions of individuals who exclusively invest in Shariah-compliant stocks, particularly in the context of the Saudi Stock Markets (SSM)?*

Under their framework, Baule et al. (2019) propose that investors may be concerned with two key aspects of a portfolio: its return and the regret associated with holding its underlying assets. In contrast to the traditional utility-based definition of regret, they present two alternative perspectives or views on this psychological construct that align with Markowitz's mean-variance framework. First, an investor may experience regret relative to the asset with the highest ex-post realized return. Second, given a mean-variance preference function, an investor may feel regretful in relation to the ex-post best realized preference value, which accounts for both risk and return. Consequently, the regret was quantified into their empirical framework based on these two distinct views.

As another alternative to solely focusing on the optimal trade-off between risk and return, investors may also consider Environmental, Social, and Governance (ESG) investing when deciding where to allocate their investments. The ESG investment framework involves analyzing environmental, social, and governance factors as non-financial elements that contribute to the valuation, performance, and risk profile of a security (Sherwood and Pollard, 2023). For instance, an environmentally aware investor concerned about climate change may choose to exclude carbon-intensive industries such as energy production, transportation, manufacturing, mining, and waste management from his/her investment portfolio. Similarly, Shariah-compliant investments can be viewed as a distinct class of ESG, adhering to the principles outlined in the Qur'an[1], Sunnah[2], and Ijtihad[3].In a manner similar to the ESG, Shariah-compliant investment strategies must align with core Islamic principles. First, the portfolio must exclude any income deemed impermissible from an Islamic perspective. Sec-

[1] The Holy Book of Islam, which is believed to be the last revelation from Allah (the God Almighty).

[2] Sunnah is the teachings and sayings of Prophet Muhammad may peace and blessing be upon him.

[3] Ijtihad is the practice of independent scholarly interpretation done by a qualified Islamic scholar (Known as Mujtahid) to derive legal rulings from the Qur'an and Sunnah for issues not explicitly addressed in primary sources.

ond, the strategy must avoid any involvement with or benefits from Riba (interest). Third, the strategy should abstain from Maysir (gambling and speculative activities) or Gharar (uncertainty or taking excessive irrational risk that might lead to total loss). Lastly, investments in industries considered unethical or harmful are not permissible (Shanmugam et al., 2009).

The Islamic finance sector and its financial instruments have emerged as a crucial component within the global financial industry. Shariah-compliant investments, in fact, have demonstrated resilience in the face of volatile global economic conditions, outperforming their conventional counterparts (Abuoliem et al., 2021; Ghaemi Asl and Rashidi, 2021). As a result, both individual and institutional investors, irrespective of their religious affiliations, have expressed growing interest in Islamic financial products (Abu-Alkheil et al., 2017). In fact, a recent report done in 2023 by the Islamic Corporation for Development of the Private Sector (ICD)[4] shows that the total Islamic finance assets reached \$4.508 trillion in 2022, of which around 22.56% concentrated in Saudi Arabia. Moreover, the ICD report projects that the global Islamic financial assets will further expand to \$6.667 trillion by 2027. The Islamic financial markets have extended their geographic reach, expanding beyond their traditional domains within Muslim-majority jurisdictions to establish a presence in Western countries, including Australia. Notably, a collaborative report[5] from The CityUK and DDCAP Group emphasizes the UK's status as the leading Western center for Islamic finance, as evidenced by the dominance of UK-based Islamic banking assets, which comprise 85% of the total European Islamic finance banking assets.

This study, in particular, contextualizes regret aversion within Islamic investing. By applying the regret-sensitive framework to the SSM, it explores how behavioural finance and religious values intersect in shaping investor decisions. It further compares Shariah-compliant and non-Shariah-compliant portfolios to quantify the opportunity cost faced by religiously motivated investors. The psychological phenomenon of regret can have significant implications for the investment decisions of some if not most Muslims in Saudi Arabia, who may be inclined to concentrate their investments in Shariah-compliant stocks to align their financial activities with their religious values. The key aim of this research is to highlight the significance of the psychological factors like regret that may influence investment decisions in Islamic financial markets, an area that has received limited attention in prior research studies. An additional objective of this research is to develop a practical mathematical model that enables investors seeking to reconcile their investment strategies with their religious beliefs. To the best of our knowledge, this study is the first to adapt the Markowitz regret model of

[4] Retrieved from $https://icd-ps.org/en/news$

[5] Retrieved from $https://www.thecityuk.com/news$

Baule et al. (2019) to an Islamic finance setting. While Baule et al. (2019) estimate regret arising from portfolio selection within a single investable universe, this research extends their framework to a context where the relevant investment universe is structurally constrained by religious principles. More precisely, it is unique in estimating the potential regret experienced by Shariah-adherent investors when excluding a distinct, non-overlapping universe of non-Shariah-compliant stocks; thereby, quantifying a type of opportunity cost that has not been formally modeled in previous literature.

The contributions of this study are fivefold. First, it quantifies the psychological cost of regret associated with investing exclusively in Shariah-compliant stocks in Saudi Arabia. Second, it analyzes how correlations between compliant and non-compliant assets influence regret-sensitive outcomes. Third, it provides insights for fund managers and policymakers into the trade-offs between ethical commitments and financial performance. Fourth, it extends the regret-sensitive Markowitz model to a novel and contextually relevant setting—Islamic financial markets. **Fifth, and most importantly, it provides a mathematical and practical framework for investors to make investment decisions that are both psychologically and financially well-judged and ethically consistent with their beliefs.**

The remaining sections of the paper are organized and formalized as follows: Section 4.2 reviews the relevant literature while Section 4.3 describes the study's data and introduces its conceptual and empirical frameworks. Section 4.4 presents and discusses the main findings of the analysis. Finally, the paper's conclusion is provided in Section 4.5.

4.2 A Glance at the Relevant Literature

Individuals often experience concerns about potential regret when making significant decisions, such as accepting a job offer, purchasing a house, selecting a medical treatment, or even making an investment. Research has demonstrated that the desire to avoid future regret can influence choices across vital areas, including negotiation process (Larrick and Boles, 1995), consumer behaviour (Simonson, 1992; Inman and Zeelenberg, 2002), medical and healthcare-related decisions (Connolly and Reb, 2003; Wroe et al., 2004), and investment related decisions (Seta et al., 2001; Muermann et al., 2006; Michenaud and Solnik, 2008; Gollier and Salanié, 2006; Baule et al., 2019). The impact of regret aversion on decision-making has been the subject of extensive scholarly investigations, dating back to the foundational developments of modern decision theory (Savage, 1951; Loomes and Sugden, 1982; Bell, 1982; Mellers et al., 1997). In this section, our paper provides a comprehensive review of the relevant literature. It first examines the pioneering studies conducted on regret aversion

Table 4.1: Demonstration of The Minimax Regret Rule

Panel A: Utility State		
Action	Rainy Day	Sunny Day
Carry Umbrella	4	5
Don't Carry	-10	10
Panel B: Relative Potential Regret State		
Action	Rainy Day	Sunny Day
Carry Umbrella	0	5
Don't Carry	14	0

Notes. This table illustrates Savage's Minimax Regret Rule. Panel A presents the utility values for two distinct actions undertaken in two different states of the world, while Panel B shows the corresponding potential regret values associated with each action under the respective states.

in a general context. Then, it proceeds to discuss the related research investigating this psychological phenomenon in the context of investment and financial-related decisions. The concluding segment in this section provides the conceptual framework guiding the current investigation and identifies the research gap in the existing literature.

4.2.1 Early Studies in Regret Aversion

The concept of regret aversion is originally proposed by Savage (1951), who asserts that individuals may take into account their potential feelings of regret or loss in the process of their decision-making. Savage (1951)'s minimax regret or loss decision rule is designed to address situations characterized by uncertainty, where the possible outcomes can be specified and determined but their probabilities are unknown. The objective of this approach is to minimize the potential post-decisional regret associated with choosing the relatively less desirable option. To illustrate the application of the minimax regret or loss rule, consider the example provided by Savage (1951), where a decision-maker must decide whether to carry an umbrella or not, anticipating two possible future states: rainy or sunny day. The decision-maker reflects upon and determines their utilities for the different outcomes, as shown in Table 4.1, Panel B. Next, they comparatively evaluate the options by calculating the relative potential regrets or losses. This involves subtracting the worse outcome utility value from the better outcome utility value for each possible state of the world. The minimax regret or loss solution in this case would be to carry the umbrella, as the maximum potential regret or loss of 14 (the regret from not carrying the umbrella if it rains) is higher than the maximum potential regret or loss of 5 (the regret from carrying the umbrella if it's sunny), and the solution is to avoid the highest possible regret value.

The economic theory of regret aversion was first formally introduced by Loomes and Sugden (1982) and Bell (1982). Loomes and Sugden (1982) defined regret as a decision-maker's post-choice reflection that their position could have been improved by selecting a different option. Similarly, Bell (1982) characterized regret as arising from making an incorrect decision, where the outcome of the chosen option is less favorable than what could have been achieved with another alternative. Their economic theory of regret posits that individuals incorporate their anticipated feelings of regret and other emotions by adjusting their utility functions. The regret theory framework accounts for the decision-maker's prospective consideration of the emotional reaction that may arise from the awareness that selecting a different alternative would have resulted in a more desirable outcome. Shortly thereafter, Bell (1985) and Loomes and Sugden (1986) proposed an additional theoretical framework known as disappointment theory. This model suggests that individuals anticipate and account for the emotion of disappointment, which arises when their realized outcome is inferior to the outcome they would have achieved under alternative circumstances. Economic regret theory and disappointment theory center on counterfactual comparisons. Regret stems from comparisons between choices, while disappointment arises from comparisons across different states of the world.

In the three theoretical frameworks we have discussed so far, anticipated emotions including regret are not directly measured but are instead hypothesized and presumed to influence decision-making process. Given that most people tend to prefer options that minimize regret, researchers like Mellers and her colleagues (Mellers et al., 1997, 1999) proposed the "Decision Affect Theory." This theory suggests that preferences are affected by the difference in outcomes between available options, which their model treats as anticipated regret. More specifically, their research indicates that emotional responses are influenced by probabilities and foregone outcomes, such that unanticipated results tend to generate stronger affective reactions than anticipated results. Through their theoretical framework, the researchers demonstrated that the selection between uncertain alternatives can be characterized as the maximization of anticipated emotional experiences. In other words, individuals tend to choose the risky option for which they expect to feel more positive on average.

Another fundamental stream of research indicates that individuals' decisions are influenced by the expected presence of some feedback regarding the outcomes of the foregone alternatives (Zeelenberg et al., 1996; Zeelenberg and Beattie, 1997). The concept here suggests that decision-makers experience less concern about potential future regret when they do not anticipate receiving any feedback on the outcomes of forgone alternatives. By shaping individuals' expectations regarding whether they will obtain information about their rejected option, their preferences towards a particular choice compared to another can be influenced. In this manner, the psychological phenomenon of regret aversion is able to provide an explanation for what may appear to be risk-averse behaviours. For example, suppose there is a choice to select between a safe and a risky alternative. Choosing the safe option typically allows individuals to avoid feedback on the risky alternative's outcome, and thus mitigate the potential for regret. Conversely, selecting the risky option exposes the decision-maker to the risk of regret should it lead to an unfavorable outcome, as they would be aware of the potential outcome had the safe alternative been chosen. However, by modifying the scenario played such that decision-makers anticipate receiving feedback on the risky option's outcome even when the safe option is selected, thereby opening the possibility of experiencing regret, their preferences may shift towards the riskier alternative (Zeelenberg et al., 1996).

4.2.2 Relevant Studies of Regret Aversion in Investment

Regret theory, a widely recognized and well-known framework in psychology and decision-making related science, has been extensively studied for its ability to address various deviations from standard utility theory. However, a key challenge lies in quantifying investors' regret in real-world financial markets, beyond the limitations of controlled experimental settings (Arisoy et al., 2024). In recent years, some research has examined the concept of investor regret and its implications in the context of portfolio selection and investment allocation process. For instance, Giove et al. (2006)'s work illustrated how security prices are modeled as interval variables within a portfolio selection problem, where a regret function based on minimax regret approach is utilized to formulate an optimal decision-making framework for portfolio selection. Instead of assuming investment returns are random (as seen in traditional models like Markowitz's mean-variance framework), their approach considers that security prices fluctuate within known intervals due to uncertainty and imprecise information. This study introduces an alternative to traditional probabilistic portfolio models, making it particularly relevant for investors facing high uncertainty and limited information. By using interval analysis and minimax regret rule, the framework proposed in Giove et al. (2006)'s work offers a robust approach to portfolio selection that does not necessitate precise knowledge of probability distributions.

Another relevant example is the work of Nwogugu (2006), which was published in the same year. He introduced in his article strategies to address investment return regrets, such as recognizing realized losses and employing framing techniques, as a method to mitigate return regret. More specifically, the author proposed quantitative frameworks that model framing effects, regret minimization, and a novel decision-making concept known as "Willingness-to-Accept-Losses." These theoretical models offer explanations for essential aspects of decision-making under conditions of uncertainty and risk. Subsequently, Li et al. (2012) developed a model that aims to minimize expected regret in portfolio selection. The model does this by minimizing the difference between the portfolio's maximum potential return and its actual return, utilizing expected regret minimization techniques.

In addition, Xidonas et al. (2017) employed a framework that minimized expected regret in portfolio selection by identifying representative points on the efficient frontier. This approach considered scenarios with future return points on the Pareto front and employed the modern economic concept of the minimax regret rule to construct the most robust investment choices. Xidonas et al. (2017) empirically evaluated the model using the Eurostoxx 50 index. Their analysis considered five distinct market scenarios based on varying historical time-periods. For each scenario, Xidonas et al. (2017) constructed the efficient frontier and computed the minimax regret solutions. The findings of this study confirm that employing the minimax regret criterion in multi-objective portfolio selection provides robust investment choices, with an increased emphasis on risk minimization.

Building on previous works, Ji et al. (2014) proposed an alternative approach to the worst-case regret optimization problem by reformulating polyhedral and conic support sets. Given that the regret minimization problem can be categorized as an NP-hard problem[6], the authors employed duality theory and semi-infinite programming techniques to reformulate the problem as a linear optimization problem, facilitating efficient computational solutions. Ji et al. (2014) evaluated their proposed model using randomly generated datasets to assess its performance in comparison to conventional regret-based optimization frameworks. The findings of their study demonstrated that the proposed method surpasses conventional regret models in terms of risk diversification. Additionally, the linear optimization formulation enhances the computational efficiency of the regret optimization problem, enabling faster solutions for large-scale scenarios. Furthermore, the worst-case regret approach results in more balanced portfolio allocations, thereby mitigating exposure to extreme risks.

Meanwhile, Li and Wang (2020) suggested a modeling approach based on the minimax regret criterion to identify robust multi-objective investment portfolios in the presence of ellipsoidal uncertainty sets with all possible scenarios, where the two objective functions were

[6] NP-hard (Non-deterministic Polynomial-time hard) problems are a classification in computational complexity theory, denoting challenges that are at least as difficult as the most complex problems in the NP complexity class. The non-deterministic polynomial (NP) time is a complexity class, denotes decision problems that can be solved in polynomial time by a non-deterministic turing machine.

the maximization of portfolio return and the minimization of mean absolute deviation (MAD) as a measure of risk. The paper presents a practical demonstration using real-world market data to validate the effectiveness of the proposed model and algorithm. Compared to the traditional robust portfolio model based on minimax robustness, the robust minimax regret optimal solutions discussed in the work of Li and Wang (2020)'s show improved performance across various evaluation criteria. However, Tsionas (2019) demonstrated that robust solutions could be obtained for the minimax regret problem, developing Monte Carlo simulation techniques without requiring the definition of specific scenarios as suggested by the previous works.

Other existing literature has also examined the theoretical implications of investor regret on portfolio selection decisions across different asset classes. For example, Muermann et al. (2006) investigated the asset allocation between low-risk and high-risk investments in defined contribution retirement plans while Michenaud and Solnik (2008)'s research examines the currency hedging decisions undertaken by investment portfolio managers, which represent a structural setting of an asset allocation problem with a single risk-free asset and a single risky asset. The findings reported in these two studies were consistent with those of Baule et al. (2019), who have demonstrated that regret-based considerations influence portfolio weights differently than the Markowitz model, depending on the distributional characteristics that make investments more or less appealing. The findings from all of the three studies suggest that when investors consider regret, they tend to avoid extreme portfolio allocations. While previous research by Muermann et al. (2006) and Michenaud and Solnik (2008) focused on two-asset problems, Baule et al. (2019)'s analysis examines the Markowitz portfolio optimization with N risky assets, as well as the case of N-1 high-risk assets along with one risk-free asset. The latter paper's findings indicate that the increased complex structure of multiple risky assets, particularly the dependence among the assets, impacts the regret risk of an investment portfolio.

An additional research that also considers a setting with multiple assets in a complete market Arrow-Debreu economy framework is the work done by Gollier and Salanié (2006). Both researchers explored optimal portfolio allocation and equilibrium asset prices in scenarios where investors are highly sensitive to regret. Gollier and Salanié (2006)'s research demonstrates that investors' regret aversion influences their optimal portfolio allocation, directing it towards assets that exhibit exceptional performance in low-probability market scenarios. Their empirical findings on the significance of asset skewness for investment attractiveness among regret-sensitive individuals were also reflected in Baule et al. (2019)'s analysis.

4.2.3 The Conceptual Basis Guiding Our Investigation and the Identified Research Gap

The theoretical framework used in this research is grounded in the work of Baule et al. (2019). They introduced a formal incorporation of regret into the Markowitz portfolio selection model, investigating how regret aversion modifies the traditional risk-return optimization process. The core elements of their model are conceptually outlined in the following three points.

1. **Portfolio Selection with Regret Aversion:** The framework incorporates regret as an additional factor for investors, who are presumed to take into account not only expected returns but also the mitigation of potential regret stemming from not selecting the best-performing asset in hindsight. Regret is conceptualized in two main ways or views. First, **Return-Regret** is when an investor may feel regret when the portfolio's realized return is lower than the highest return among the available investment alternatives. The second view is **Preference-Regret**, which is the approach that accounts for regret in relation to both return and risk. This is when an investor feels remorse for not selecting the portfolio with the most favourable risk-adjusted return.

2. **Adjustment in Risk Assessment:** The model proposed incorporates a regret-adjusted variance that alters the covariance matrix utilized in the optimization process. This modification results in two alternative optimization strategies. The first approach is the **return-regret-adjusted covariance matrix** which focuses solely on adjusting the returns. The second approach is **preference-regret-adjusted covariance matrix** which combines both classical risk (variance of returns) and regret risk when running the adjustment. Another factor that the empirical model incorporates is an additional parameter, denoted as α, that reflects the investor's degree of regret aversion. This parameter is utilized when computing both the return-regret-adjusted and preference-regret-adjusted variance-covariance matrices. The inclusion of this parameter enables the optimization process to generate portfolio weights that are sensitive to the investor's level of regret, while maintaining the overall tractability of the original optimization framework.

3. **Implications for Portfolio Composition:** Through this adjusted model, investors can adhere to a classical mean-variance framework while incorporating regret considerations. This adjustment may lead to overweighting or underweighting of specific assets based on their correlation with the ex-post best-performing investment option. Consequently, the portfolio composition may deviate from the Markowitz efficient frontier, reflecting an

equilibrium between risk, return, and regret, rather than a pure risk-return optimization approach.

The framework introduced by Baule et al. (2019) offers practical applicability by allowing investors to integrate regret into their portfolio decision-making process, with minimal modification to existing methods. This approach provides an avenue for optimizing portfolios under psychological considerations that extend beyond traditional risk and return criteria.

In the same context, our research paper aims to build upon the conceptual and empirical frameworks established by Baule et al. (2019), with a minor modification. Instead of solely examining regret within an investor's own investable universe with a limited set of assets and solving the problem for the optimal allocation, the focus will be expanded to include larger asset sets and estimate the potential regret that may arise from a distinct, non-overlapping un-investable universe, such as a non-Shariah-compliant universe, for an investor strictly concentrated on Shariah-compliant investments. This framework assumes the presence of two distinct, non-overlapping investable and un-investable universes within the overall market universe, encompassing all investable and non-investable assets. For instance, in Figure 4.1, the overall market contains 10 financial assets, of which 4 are Shariah-compliant and 6 are non-Shariah-compliant. In our study, we will estimate the regret associated with limiting investment choices to the Shariah-compliant universe, which includes only 4 assets in our hypothetical example, and excluding the non-Shariah-compliant assets from the investment portfolio. Furthermore, the study will assess the regret associated within the Shariah-compliant universe as seen in the original framework by Baule et al. (2019). Therefore, the analysis incorporates two types of regret: regret due to the selection of Shariah-compliant assets over non-Shariah-compliant assets, and regret due to the selection of one Shariah-compliant asset over another Shariah-compliant asset.

This research paper contributes to a couple of academic disciplines. For example, it belongs to the academic literature on behavioural portfolio theories, which examines portfolio optimization problems involving non-traditional investor preferences, such as regret, loss, and disappointment aversions, as well as mental accounting principles (Shefrin and Statman, 2000; Ang et al., 2005; Driessen and Maenhout, 2007; Das et al., 2010; Shi et al., 2015). Furthermore, it also aligns with the literature on Islamic finance and portfolio optimization involving Shariah-compliant investments (Wilson, 1997; Derigs and Marzban, 2009; Arouri et al., 2013).

This research holds significant relevance given the sizeable Muslim population and the substantial volume of Islamic financial investments globally. According to Pew Research

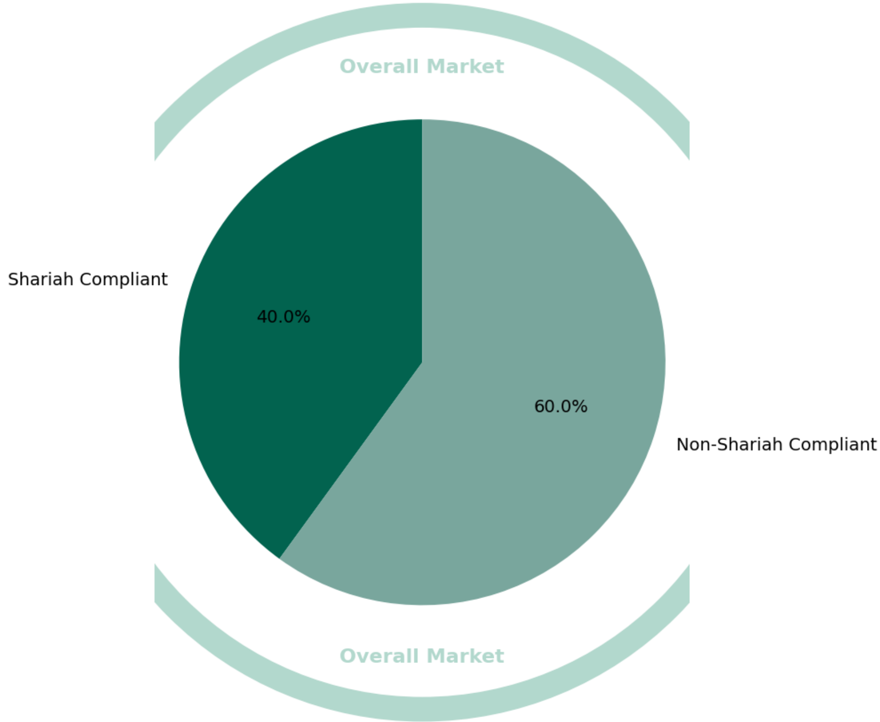


Figure 4.1: Illustration of a Financial Market Universe and Its Subsets

projections[7], the worldwide Muslim population is expected to experience rapid growth, rising from approximately 1.6 billion in 2010 to nearly 2.8 billion by 2050, representing a shift from 23.2% to 29.7% of the global population. Furthermore, a recent report published by the ICD[8] indicates that the combined value of Sukuk and Islamic Investment Funds worldwide exceeded $1 trillion in 2022.

To the best of our knowledge, this study represents a pioneering effort to apply the Markowitz regret model, developed by Baule et al. (2019), to estimate the potential regret faced by investors who construct portfolios solely using Shariah-compliant assets while excluding non-Shariah-compliant assets (Reflected within a distinct, non-overlapping investment universe). Applying the techniques outlined in this research, investors may be able to determine the optimal asset allocation that minimizes their regret over not investing in the non-Shariah-compliant investment universe. The following section provides a detailed discussion of the empirical approach used in this research.

[7] Retrieved from https://www.pewresearch.org/religion/2015/04/02/religious-projections-2010-2050/

[8] Retrieved from https://icd-ps.org/en/news.

4.3 Data Description and Empirical Framework

4.3.1 Data Characteristics and Analysis

The study utilizes daily closing prices for all publicly traded stocks on the main Saudi stock exchange for the years 2018 and 2023. The financial data is obtained from the official website of the Saudi Stock Exchange. This study also uses the daily U.S. Treasury real long-term rates as the measure for risk-free rates collected from the US treasury department website[9]. This decision was made due to the absence of an established index representing risk-free rates in the relatively young Saudi debt market. Furthermore, the study considered the close alignment between the Saudi currency and the U.S. dollar, as Saudi Arabia's monetary policy adheres to a fixed-exchange regime pegged to the U.S. dollar. Regarding the Shariah-compliant classification of the stocks, the analysis primarily relies on the Shariah-compliant financial assessments conducted by Dr. Mohammed Al-Osaimi and published on his Almaqased website[10]. Dr. Al-Osaimi's team of religious scholars and experts provide a highly regarded classification of the securities traded on the SSM. For any stock not evaluated by Dr. Al-Osaimi and his team, the Shariah-compliant status is determined using the Shariah-compliant list maintained by Alrajhi Capital and Albilad Capital, covering both study periods.

The fundamental principles underlying Shariah-based evaluations, which form the basis for most religious rulings (Fatwas) as per the Sharia boards and AAOIFI standards, are outlined in the following three points:

1. The nature of the company's business activities.
2. The company's use of conventional loans.
3. The percentage of prohibited returns on the company's investments.

The Shariah classification of listed joint-stock companies, according to the prevailing views of most Islamic scholars, can be classified into four primary categories. The four Shariah-compliant classifications are detailed below with a brief description of each category.

1. **Companies engaged in prohibited activities (Classified as Activity Not Complaint in our analysis)** are those whose primary operations are impermissible under Shariah law, even if they fund or invest in permissible ventures, such as conventional commercial banking activities.

[9] Retrieved from $https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics/legacy-interest-rate-xml-and-xsd-files$

[10] Retrieved from $https://almaqased.net/$

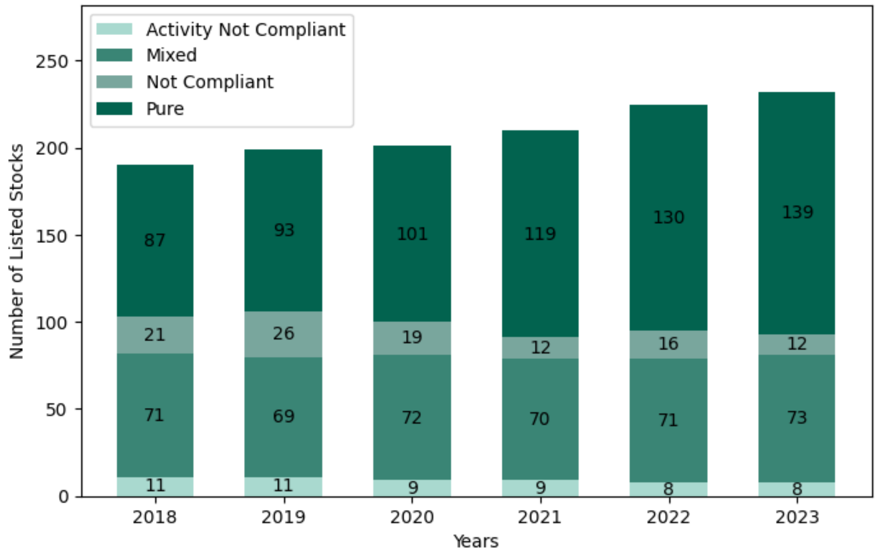


Figure 4.2: Number of Listed Stock Per Shariah Compliant Classification

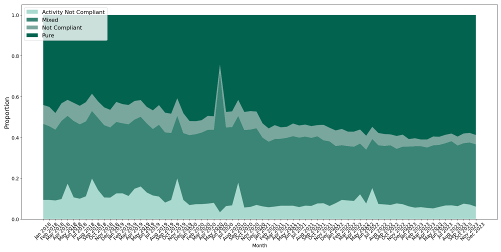
2. **Companies that fail to satisfy the Shariah-compliance criteria (Classified as Not Complaint in our analysis)** are those that engage in permissible business activities but have borrowed or invested in prohibited elements exceeding one-third of their total assets or liabilities and shareholder equities, and/or derive prohibited income exceeding 5% of their total revenue.

3. **Mixed companies (Classified as Mixed in our analysis)** are those that engage in permissible business activities but have certain prohibited elements in their capital structure or revenue composition. Specifically, such companies may have borrowed funds that do not exceed one-third of their total liabilities and may derive prohibited income that does not surpass 5% of their total revenue.

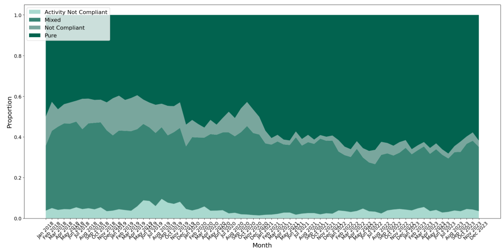
4. **Pure companies (Classified as Pure in our analysis)** are those that conduct their business activities in a manner that adheres to the principles and guidelines of Islamic law, without engaging in any prohibited investments or financing arrangements (although there may be a slight excess, such as 1%).

After organizing and grouping the listed stocks on the SSM into the four Sharia-compliant categories, the data indicates a decline in the number of stocks denoted as Activity Not Compliant and Not Compliant, from 32 stocks in 2018 to approximately 20 stocks in 2023. On the other hand, the number of stocks categorized as Pure and Mixed Shariah-compliant increased from 87 stocks and 71 stocks respectively in 2018, to around 139 stocks and 73 stocks in 2023 (See Figure 4.2).

In terms of the trading activity in the SSM, the data indicates that the monthly average share of trades for the category classified as "Pure" Shariah-compliant has increased by 20.3 percentage points, from 43.2% in 2018 to 63.5% in 2023. Correspondingly, the monthly average share of trades in the SSM for the remaining Shariah-compliant and Non-Shariah-compliant categories has decreased from 56.8% in 2018 to 36.5% in 2023. A similar pattern is observed in the monthly average share of value traded in the SSM. The monthly average share of value traded per trade in the SSM for the "Pure" Shariah-compliant category has grown by 15.7 percentage points, from 43.8% in 2018 to 59.5% in 2023, while the monthly average share of value traded per trade in the SSM for the other Shariah-compliant and Non-Shariah-compliant categories has declined from 56.2% in 2018 to 40.5% in 2023 (Refer to Figure 4.3).



(a) Share of Value Traded Per Classification



(b) Share of Trades Per Classification

Figure 4.3: Trade and Value Traded Activities Per Classification

Given that the majority of stocks listed on the SSM in the two years of the study periods are classified as Pure and Mixed Shariah-compliant, and they account for the largest significant shares in terms of trade volume and value traded per trade compared to the other Non-Shariah-compliance categories, this paper examines two distinct types of investor or investment scenarios in its optimization analysis based on the adherence to Islamic Shariah principles. The first scenario represents a Strict Shariah Adherent investor, who allocates his/her portfolio solely to stocks classified as "Pure" Shariah-compliant, excluding all other classifications considered part of the non-Shariah-compliant investment universe ($U2$). The second scenario considers a Moderate Shariah Adherent investor, who includes both "Pure" and "Mixed" Shariah-compliant stocks in their portfolio construction process, while treating the remaining categories as non-Shariah-compliant assets (See Figure 4.4). Therefore, this paper aims to solve the optimization problem by analyzing the two investment scenarios or investor types and assessing the impact of regret on the optimal asset allocations for each scenario or type of Shariah-adherent investor.

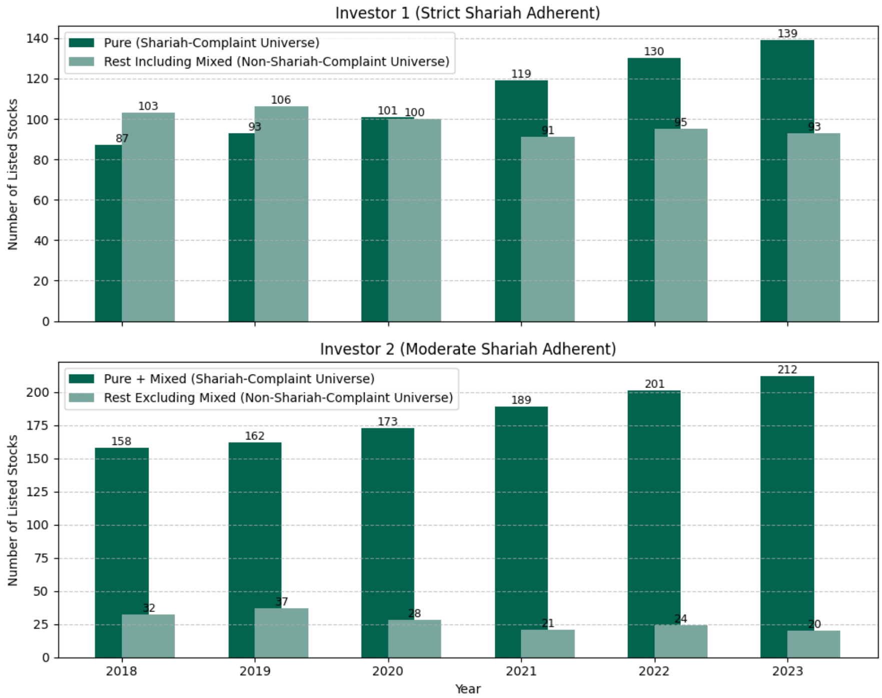


Figure 4.4: Invesetable and Non-investable Universes for the Study's Scenarios

4.3.2 Empirical Approach Employed in this Study

In this empirical work, we investigate a two-period investment selection problem for two distinct investment scenarios. The first scenario involves a Strict Shariah Adherent investor who constructs a portfolio solely from stocks classified as Pure Shariah-compliant. The second scenario considers a Moderate Shariah Adherent investor who includes both Pure and Mixed Shariah-compliant stocks in his/her portfolio. The two types of investors evaluate investment selections based on two criteria. The first criterion is return, as in traditional portfolio selection, representing the benefits of investment and consumption opportunities. The second criterion is the mitigation of regret, representing the emotional and self-expressive advantages of being close to the ex-post optimal choice, either from their set of Shariah-compliant stocks or from the non-Shariah-compliant set of stocks. The empirical framework utilized in this paper is grounded in the regret-based extension of the Markowitz model proposed by Baule et al. (2019). Within this framework, the authors retain the use of the Sharpe ratio rather than alternative metrics due to its compatibility with the mean-variance structure of the model. This choice preserves analytical tractability, allows for regret to be incorporated via adjustments to expected returns or the covariance matrix, and ensures interpretability by maintaining alignment with established portfolio performance measures. As such, the Sharpe ratio serves as a natural and effective tool in evaluating investment portfolios under regret-augmented mean-variance optimization.

The classical Markowitz optimization framework aims to determine the optimal portfolio allocations based on the first criterion, which focuses on the mean and variance of returns. In this framework, a portfolio P consisting of N risky assets has an expected return R_P and variance σ_P^2, which are defined in the following equations (4.1) and (4.2):

$$R_p = \sum_{i=1}^{N} \omega_i R_i = \omega^T \mathbf{R} \tag{4.1}$$

$$\sigma_P^2 = \omega^T \Sigma \omega \tag{4.2}$$

where:

- ω_i represents the weight variable of an asset i in an investment portfolio P,
- R_i denotes the expected return variable of an asset i in an investment portfolio P[11],
- ω represents the weight vector of an investment portfolio P,
- $\mathbf{R}$ denotes the vector of expected returns of an investment portfolio P,
- Σ is the covariance matrix of asset returns.

The portfolio optimization problem aims to determine the optimal portfolio weights ω_i by either minimizing risk for a given expected return or maximizing return subject to a risk constraint. Within the mean-variance optimization framework, the problem can be formulated as minimizing portfolio variance ($\omega^T \Sigma \omega$) while achieving a target return ($\omega^T \mathbf{R} = R_p$) and ensuring full investment through the budget constraint ($\omega^T \mathbf{1} = 1$). Alternatively, the objective can be to maximize expected return ($\omega^T \mathbf{R}$) while keeping portfolio variance below a specified risk level ($\omega^T \Sigma \omega \leq \sigma_P^2$). Additional constraints, such as non-negative weights for long-only portfolios (Short selling option is not allowed, such that $\omega_i \geq 0$) or individual asset allocation limits, can be incorporated as needed. These formulations, which form the basis of Modern Portfolio Theory, enable investors to construct an efficient frontier and optimize their portfolios based on their risk-return preferences (Brooks, 2019).

Regarding the treatment of regret (Related to the second criterion), the existing literature commonly defines regret as the difference in utility between the selected investment and the ex-post best alternative. However, since the primary analytical approach employed in this empirical work is the mean-variance optimization analysis, rather than the traditional expected utility maximization framework, the utilized model proposed by Baule et al. (2019)

[11] The daily return of each individual stock is calculated as ($R_{i,t} = ln\left[\frac{P_{i,t}}{P_{i,t-1}}\right] \times 100$), where, $R_{i,t}$ represents stock *(i)*'s return on day *(t)*, ln is the natural logarithm, $P_{i,t}$ indicates the closing price for stock *(i)* on day *(t)*, and $P_{i,t-1}$ represents the closing price of stock *(i)* on the previous trading day *(t-1)*.

incorporates regret by defining a "regret-adjusted return (Z_i)", which combines the investment return and a regret term. This regret term represents the difference between the chosen investment's performance and the highest performance among the available investment alternatives in hindsight. The regret-adjusted return (Z_i) can be expressed as shown in the following equation (4.3).

$$Z_i = (1 - \alpha)R_i - \alpha \, \text{Regret}_i \tag{4.3}$$

where:

- $\alpha \in [0, 1]$ represents the investor's degree of regret aversion,
- Regret_i is the regret value, which varies depending on the regret view or type.

As discussed earlier, Baule et al. (2019) employ two distinct approaches to incorporating the regret factor in their framework. The first view focuses solely on "Return-Regret," positing that the perception of regret is driven by realized returns, rather than risk considerations. They argue that once returns are realized, the uncertainty surrounding the investment decision is eliminated. The second view is the "Preference-Regret" approach, which considers both the realized returns and the variances in determining the perception of regret. In this view, an investor has a preference function[12] that relates expected return of an investment and its variance. For the perception of regret, the investor compares the realized preference value of the chosen investment to the ex-post optimal preference value among all alternative investments. The authors posit that an investor feels less regret towards a subsequent well-performing investment if it was not a good choice prior to the investment decision due to a low preference value caused by high risk.

In this paper, we assess the potential regret (based on both views) experienced by investors who construct their portfolios using only Shariah-compliant assets, while excluding non-Shariah-compliant assets from their investable universe. We evaluate regret from two standpoints: First, within the Shariah-compliant universe ($U1$), reflecting potential regret within the investor's own investable set. Second, against the non-Shariah-compliant universe ($U2$), capturing potential regret from excluding those non-investable assets, which represent a distinct, non-overlapping uninvestable universe.

As an initial phase, we establish two separate, non-overlapping investment universes based on our investment scenarios (Strict Shariah Adherent Investor Vs. Moderate Shariah Adher-

[12] Let $\pi(.)$ indicates a preference function, which is commonly defined as $\pi(\mu_i, \sigma_i^2) = \mu_i - \gamma\sigma_i^2$. Here, μ_i denotes the expected return of asset i, σ_i^2 is the variance of returns of that asset i, and γ represents the risk aversion coefficient, which is ≥ 0.

ent). Subsequently, we assess the two forms of regret after determining the maximum return and preference value within each universe. The return-regret approach defines regret as the difference between the selected investment's return and the highest realized return across all available investment alternatives, as specified in the equation (4.4).

$$\text{Regret}_{i,t,\text{ret}} = R_{\text{u},t,\max} - R_{i,t} \tag{4.4}$$

On the other hand, the preference-regret viewpoint considers both return and risk, defining regret as the deviation from the "preference value" - a measure that balances these two factors. In this empirical study, where individual stocks are examined, the paper employs a moving average approach to calculate the preference value based on the previous 30 trading days' returns and variances[13]. The regret is then quantified as described in equation (4.5).

$$\text{Regret}_{(i,t,\text{pref})} = \pi(\mu_{30,t,u}, \sigma^2_{30,t,u})_{max} - \pi(\mu_{30,t}, \sigma^2_{30,t})_i \tag{4.5}$$

where:

- $R_{\text{u},t,\max}$ represents the daily maximum return observed across all assets in a universe u at trading day t[14],
- $R_{i,t}$ denotes the daily return variable of an individual asset i on a trading day t,
- $\pi(\mu_{30,t,u}, \sigma^2_{30,t,u})_{max}$ is the daily maximum preference value observed across all assets in a universe u at trading day t calculated based on a widow of the previous 30 trading days,
- $\pi(\mu_{30,t}, \sigma^2_{30,t})_i$ denotes the daily preference value of an individual asset i on trading day t computed based on the previous 30 trading days.

Incorporating the computed regret measures into the formulation of the return-regret-adjusted return ($Z_{i,ret}$), as outlined in equation (4.6), and the preference-regret-adjusted return ($Z_{i,pref}$), as specified in equation (4.7).

$$Z_{i,ret} = R_i - \alpha \, R_{\text{u},t,\max} \tag{4.6}$$

$$Z_{i,pref} = \mu_{30,i,t} - \alpha \, \pi(\mu_{30,t,u}, \sigma^2_{30,t,u})_{max} - \alpha\gamma\sigma^2_{30,i,t} \tag{4.7}$$

[13] To calculate both the 30-day moving average stock return and variance, we use the following two equations. First, the 30-day Simple Moving Average of Return is given by $\mu_{30} = \frac{1}{30}\sum_{i=1}^{30} R_i$. Then, the 30-day Rolling Variance is computed by $\sigma_{30} = \frac{1}{30}\sum_{i=1}^{30}(R_i - \mu_{30})^2$.

[14] If the regret is assessed against the investor's own Shariah-Complaint investable universe ($U1$), the maximum return would be $R_{\text{U1},\max} = \max(R_{\text{U1},1}, R_{\text{U1},2}, \ldots, R_{\text{U1},N})$. However, if the regret assessment is conducted against the non-Shariah-compliant universe ($U2$), the maximum return would be $R_{\text{U2},\max} = \max(R_{\text{U2},1}, R_{\text{U2},2}, \ldots, R_{\text{U2},N})$.

Now, this paper proceeds to further discuss the shift from the classical Markowitz optimization framework to the regret-augmented optimization approach. In the classical Markowitz optimization model, the objective is to select portfolio weights ω that maximize the investor's utility by balancing the expected return and risk of his/her Shariah Complaint investment portfolio. This can be expressed as described in equation (4.8).

$$\max_{\omega} \left[E(R_P) - \gamma \operatorname{Var}(R_P) \right] \tag{4.8}$$

where:

- $E(R_P)$ denotes the expected returns of the Shariah Compliant investment portfolio,
- $\operatorname{Var}(R_P)$ represents the Shariah Complaint investment portfolio's variance,
- γ is the risk aversion coefficient, reflecting the investor's risk tolerance level.

In this setup, a higher value of risk aversion coefficient γ reflects greater risk aversion, which drives the optimization toward portfolios with lower variance.

On the other hand, the regret-augmented optimization approach incorporates an additional term or factor that reflects regret, specifically addressing the investor's aversion to realizing, in hindsight, that an alternative investment would have performed better. This regret sensitivity is incorporated using the regret-adjusted return Z_i, as defined previously in equation (4.3). The coefficient α here indicates the level of regret aversion, with zero value indicating the absence of regret (Markowitz case) and a higher value of one leading to the extreme regret case. Thus, the regret-augmented optimization problem is as specified in equation (4.9).

$$\max_{\omega} \left[E(Z_P) - \gamma \operatorname{Var}(Z_P) \right] \tag{4.9}$$

where:

- $E(Z_P)$ denotes the expected regret-adjusted returns of the Shariah Compliant investment portfolio,
- $\operatorname{Var}(Z_P)$ represents the Shariah Complaint investment portfolio's regret-adjusted variance,
- γ is the risk aversion coefficient.

This formulation described in equation (4.9) resembles the classical approach, yet it integrates alterations to both the expected return and the variance components. The investor's goal here is to maximize the expected regret-adjusted return $E(Z_P)$ while minimizing the regret-adjusted variance $\operatorname{Var}(Z_P)$, which means maximizing a regret-adjusted utility. The optimization can be performed using either the return-regret-adjusted return $(Z_(P, ret))$ or the preference-regret-adjusted return $(Z_(P, pref))$, as the objective function specified in the following equation (4.10).

$$\max_{\omega} \left[E(R_P) - \alpha\, \mathrm{E}\left(Regret_{P,u}\right) - \gamma\, \mathrm{Var}(R_P - \alpha Regret_{P,u})\right] \tag{4.10}$$

The utility function employed in this framework includes the following key elements:

- Expected return $E(R_P)$, which Shariah-complaint investors seek to maximize,
- Regret expectations $\mathrm{E}\left(Regret_{P,u}\right)$, which Sharaih-complaint investors seek to mitigate from universe u,
- Variance of the regret-adjusted portfolio returns $\mathrm{Var}(R_P - \alpha Regret_{P,u})$, which captures the risk associated with potential regret assessed from universe u[15].

When interpreting the outcome of this regret-augmented optimization framework, if the regret aversion coefficient α is set to zero, the model reverts to the classical Markowitz portfolio optimization approach, without any adjustments for regret considerations. Alternatively, as the regret aversion coefficient α increases, regret becomes more prominent in the optimization process. Consequently, the optimization prioritizes the selection of investments that mitigate the risk of substantial underperformance relative to the best-performing alternative investment. Depending on the investor's perspective on regret, the optimization may result in more conservative or diversified portfolio compositions.

Throughout the portfolio optimization process with regret, Baule et al. (2019)'s framework suggests two alternative methods to incorporate regret risk considerations into the optimization process, either by modifying the covariance matrix or adjusting the expected returns. The conventional covariance matrix (Σ) is substituted with a regret-adjusted covariance matrix (Σ_{ra}) that accounts for the regret adjustment based on either return-regret or preference-regret. It is, then, simultaneously utilized alongside the unadjusted vector of expected returns to identify the optimal portfolio allocations. Alternatively, the expected return vector $(E(R_P))$ is adjusted by incorporating a regret-based component to get the expected regret-adjusted return vector $(E(Z_P))$[16]. To determine the optimal portfolio weights,

[15] When the regret term is assessed based on Preference View, the regret-adjusted portfolio's return variance $(\mathrm{Var}(R_P - \alpha Regret_{P,u}))$ reflects the risk from both the traditional investment risk as well as the potential regret tied to the portfolio's performance against the best-performing asset observed in universe u.

[16] The new (regret-adjusted) vector of expected returns is given as specified in the following equations: Under return-regret view, the equation is $\tilde{\mu}_{\mathsf{ra}}^{\mathsf{ret}} = \mu + 2\alpha\gamma\, \mathrm{Cov}(R_P, R_{\max})$. Alternatively, the equation is $\tilde{\mu}_{\mathsf{ra}}^{\mathsf{pref}} = \mu + 2\alpha\gamma\, \mathrm{Cov}(R_P, \pi_{\max})$, under preference-regret view. From these equations, $\mu = E[R]$ denotes the vector of (classical) expected returns, $\mu_{ra} = E[Z]$ represents the vector of (regret-adjusted) expected returns, and it differs under the return-regret view and preference regret view, $\mathrm{Cov}(R_P, R_{\max})$ is the classical covariance matrix between portfolio return and best-performing investment return, $\mathrm{Cov}(R_P, \pi_{\max})$ is the

the modified vector of expected returns $E(Z_P)$ is simultaneously employed with the classical return covariance matrix derived from the original returns (Σ).

In this empirical study, we employ the first approach, where the covariance matrix is adjusted to determine the optimal portfolio weights while accounting for various types of risk, including regret that arises from not investing in other better-performing Shariah-compliant assets or non-Shariah-compliant assets. Consequently, the optimal portfolio weights can be determined using the standard $\mu - \sigma^2$ optimization framework, where the regret-adjusted covariance matrix between the return of a Shariah-compliant investment portfolio P constructed from universe 1 is paired with an unadjusted vector of its expected returns. In addition, the optimization problem includes short-selling constraints, where $\omega_i \geq 0 \quad \forall i$, while also satisfying the budget constraint to ensure complete investment allocation $(\omega^T \mathbf{1} = 1)$. The non-negativity restrictions on leverage are necessary because short selling for individual stocks is not yet permitted in the SSM. Additionally, the ex-post best strategy, which involves short-selling the worst-performing asset with unlimited capital, would result in infinite wealth. However, this strategy is neither realistic nor a meaningful benchmark for an investor's regret, as it is not a practical or achievable investment approach (Baule et al., 2019).

The regret-adjustment process of the covariance matrix depends on the specific perspective of regret being considered. Based on return view of regret, the regret-adjusted covariance matrix is given as

$$\tilde{\Sigma}^{\mathsf{ret}} = \Sigma^{\mathsf{ret}}_{\mathsf{ra}}$$

whereas a combined matrix under preference-regret view is given by

$$\tilde{\Sigma}^{\mathsf{pref}} = \alpha\Sigma + \Sigma^{\mathsf{pref}}_{\mathsf{ra}}$$

Where,

- $\Sigma = (\mathrm{Cov}(R_i, R_j))_{i,j}$, which is the classical covariance matrix,
- $\Sigma_{\mathsf{ra}} = (\mathrm{Cov}(Z_i, Z_j))_{i,j}$, that is the regret-adjusted covariance matrix, and it differs under the return-regret view (Z_P^{ret}) and preference regret view (Z_P^{pref}) as described in the equations.

This research utilizes Operations Research (OR) techniques[17] to solve its portfolio opti-

classical covariance matrix between portfolio return and best-performing investment's return based on its preference value.

[17] Operations Research (OR) is an area of study that employs analytical and mathematical techniques to tackle decision-making, optimization, and problem-solving in complex contexts. This discipline of study utilizes mathematical modelling, statistical analysis, and algorithmic approaches to optimize processes, enhance

mization problem. More specifically, our paper follows a Monte Carlo Simulation based on Markowitz Mean-Variance Optimization framework, integrating the classical optimization and regret-based views assessed from two distinct, non-overlapping universes (Shariah-complaint and Non-Shariah-complaint) focusing on our two investment scenarios (Strict Shariah Adherent Investor Vs. Moderate Shariah Adherent) for two year periods (2018 and 2023). First, the Classical Markowitz Model with the absence of regret is applied ($\alpha = 0$), where about 10 thousand random portfolios (comprising 15, 30, or 40 assets) are generated using Monte Carlo Simulation, and their annualized expected return, variance, and Sharpe Ratio are computed. The optimization is performed using Sequential Least Squares Programming (SLSQP) to maximize the Sharpe Ratio, ensuring full investment ($\omega^T \mathbf{1} = 1$) and no short selling ($\omega_i \geq 0 \quad \forall i$). The efficient frontier is then analyzed to determine the Maximum Sharpe Ratio Portfolio ($\mu - \sigma$, highest risk-adjusted return portfolio) and the Minimum Variance Portfolio (Min-Var, lowest risk portfolio).

This study's second phase employs regret-adjusted optimization[18], where regret is evaluated from two viewpoints (Return View and Preference View). First, regret is assessed under Return View once against the Shariah-Compliant investment universe ($U1$). Then, it is assessed against the Non-Shariah-Compliant universe ($U2$). The portfolio optimization is conducted under both scenarios, incorporating regret adjustments that account for underperformance relative to the best-performing stock in each benchmark universe. Accordingly, the regret-adjusted covariance matrices are modified, leading to an alternative set of efficient portfolios that reflect regret considerations. After solving the portfolio problem under Return View, the assessment proceeds to the Preference Regret View, which incorporates investor preference-based regret. Here, the optimization is also conducted separately for $U1$ (Shariah-complaint) and $U2$ (Non-Shariah-complaint) to evaluate how regret influences portfolio composition when preferences and constraints vary.

In summary, the regret-augmented optimization process integrates behavioural considerations, ensuring that the resulting portfolios align with investor choices, risk aversion, and psychological biases. The empirical analysis in this paper provides a comprehensive evaluation of portfolio selections, transitioning from a pure return-risk tradeoff to an investor-centric, behaviourally-adjusted strategy that incorporates both regret-based return assessment and

efficiency, and maximize performance outcomes. OR is extensively applied across diverse industries, including manufacturing, transportation, healthcare, supply chain and finance, to support organizations in making more informed decisions grounded in data-driven and quantitative models.

[18] Consistent with the approach adopted in the initial phase, 10,000 random portfolios were generated through Monte Carlo simulation, and their annualized expected return, regret-adjusted risk, and Sharpe ratio were computed. The optimization technique employed was also similar to that utilized in the preceding step, wherein the SLSQP algorithm was applied with the same set of constraints.

preference-driven regret adjustments.

4.4 Empirical Results and Interpretation

In this section, the paper first discusses key characteristics of the daily average returns for the overall market, the Shariah-compliant universe ($U1$), and the Non-Shariah-compliant universe ($U2$) across the study's investment scenarios. It then presents and discusses the empirical findings from the portfolio optimization problem, covering the estimated return distribution and optimal portfolio allocation under regret considerations[19].

4.4.1 Key Characteristics of the Daily Average Stock Returns

Table 4.2 presents the daily average return characteristics for 2018 and 2023. The statistical data in the table reveals significant changes in market performance, investment strategy outcomes, and the comparative behaviour of Shariah-compliant ($U1$) and Non-Shariah-compliant ($U2$) stocks between these two years. In 2018, the overall market exhibited a negative mean return of -0.039% and a relatively high standard deviation of 0.841%, indicating substantial volatility. However, by 2023, the market had improved considerably, with a positive mean return of 0.082% and a reduced standard deviation of 0.606%, suggesting a more stable investment environment. A key observation is the consistent difference between Shariah-compliant and Non-Shariah stocks. In both years, the Non-Shariah ($U2$) stocks exhibited greater volatility compared to the Shariah-compliant ($U1$) stocks. For example, in 2018, Non-Shariah stocks under a strict Shariah adherence investment style ($S1$) had a mean return of -0.045% and a standard deviation of 0.944%, whereas Shariah stocks had a slightly better mean return of -0.032% and lower volatility at 0.751%. By 2023, the trend shifted, with the Non-Shariah ($U2$) stocks under the same investment style ($S1$) outperforming the Shariah-compliant ($U1$) stocks in terms of mean return, but remaining riskier with a higher standard deviation.

When evaluating different investment strategies, it becomes evident that a strict adherence to Shariah principles ($S1$) resulted in relatively stable but slightly lower returns compared to a moderate adherence investment style ($S2$). In 2018, the moderate adherence strategy for Shariah-compliant stocks ($S2$) yielded a negative return of 0.047%, while by 2023, it had generated a slightly high of 0.084% mean return compared with the strict adherence

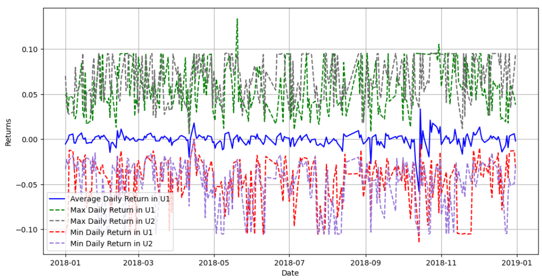
[19] This paper conducts some further investigations related to the impact of regret aversion sensitivity on stock return adjustment at the individual stock level. Their related key findings can be found in the appendices.

Table 4.2: Daily Average Return Characteristics

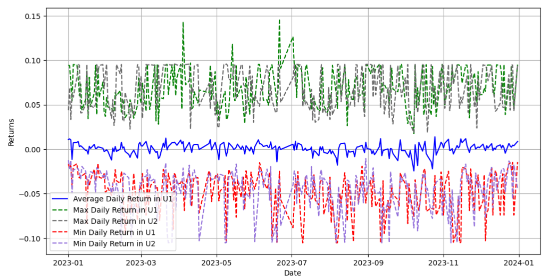
Year	Scenario	Universe	Mean (%)	Std. Dev (%)	Median (%)	Max (%)	Min (%)	Range	Obv.	Underlying Stocks
2018	Overall Market		-0.039	0.841	0.023	3.710	-6.456	10.167	249	190
	Investor 1: Strict Shariah Adherent	U1 - Shariah	-0.032	0.751	0.017	3.359	-5.809	9.168	249	87
		U2 - Non-Shariah	-0.045	0.944	0.026	4.007	-7.003	11.010	249	103
	Investor 2: Moderate Shariah Adherent	U1 - Shariah	-0.047	0.818	0.017	3.718	-6.431	10.148	249	158
		U2 - Non-Shariah	0.001	1.062	0.040	3.674	-6.583	10.257	249	32
2023	Overall Market		0.082	0.606	0.142	1.359	-2.606	3.965	249	232
	Investor 1: Strict Shariah Adherent	U1 - Shariah	0.067	0.607	0.114	1.386	-2.449	3.835	249	139
		U2 - Non-Shariah	0.103	0.665	0.192	1.345	-2.841	4.186	249	93
	Investor 2: Moderate Shariah Adherent	U1 - Shariah	0.084	0.608	0.143	1.353	-2.642	3.995	249	212
		U2 - Non-Shariah	0.054	0.750	0.131	2.251	-2.375	4.626	249	20

Notes. This table presents statistical data on the daily average returns for the various investment scenarios and universes examined in the study over the 2018 and 2023 periods. The statistical indicators reported include the mean, standard deviation, median, maximum, minimum, and range of the daily returns, as well as the number of observations and underlying stocks for each category.

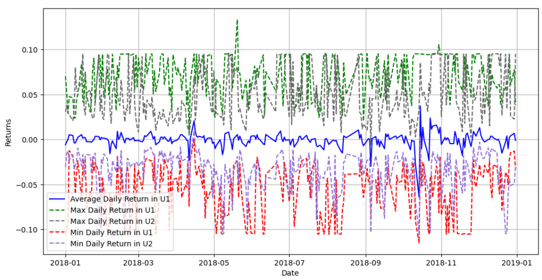
style ($S1$), though with slightly greater volatility in both periods. The graphical analysis given in Figure 4.5 further demonstrates that Non-Shariah-compliant stocks consistently exhibited more substantial fluctuations, with higher peaks and deeper drawdowns compared to Shariah-compliant stocks. However, the daily maximum and minimum average returns of the Non-Sharaih-complaint stock observed in the moderate adherence investment style ($S2$) displays lower levels of fluctuation than the Shariah-complaint stocks compared with what has been seen in the strict adherence investment style ($S1$). By looking at Table 4.2, the data suggests an overall decline in market volatility over time, as evidenced by the reduced range of maximum and minimum daily returns in 2023 relative to 2018.



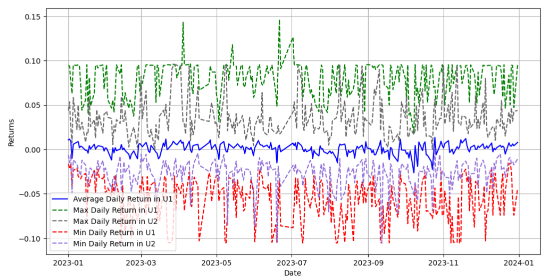
(a) Return Indicators in $U1$ and $U2$ for $S1$ (2018)



(b) Return Indicators in $U1$ and $U2$ for $S1$ (2023)



(c) Return Indicators in $U1$ and $U2$ for $S2$ (2018)



(d) Return Indicators in $U1$ and $U2$ for $S2$ (2023)

Figure 4.5: Statistical Indicators of Daily Stock Returns for Universe 1 & 2

Overall, based on the data of return analysis, the findings illustrate a clear trade-off between risk and return. Shariah-compliant investments offered a more stable and predictable return profile, making them more attractive to risk-averse investors. In contrast, non-Shariah stocks exhibited higher risk but also the potential for greater returns. The broader market trend between 2018 and 2023 suggests an improvement in financial conditions, with increased returns and reduced volatility, benefiting all investor categories. Ultimately, the choice between investing in Shariah-compliant or non-Shariah stocks depends on the investor's risk tolerance, with Shariah adherence providing stability and risk mitigation, while non-Shariah investments present higher return opportunities at the cost of increased uncertainty. Therefore, the potential for higher returns associated with non-Shariah stock investments may lead to a sense of regret among investors who choose to allocate their investments solely to Shariah-compliant stocks.

4.4.2 Analysis of the Optimization Results

This sub-section discusses the results of the study's portfolio optimization problem with regret, considering a comparison between two Shariah-compliant investment scenarios (Strict Shariah Adherent Investors vs. moderate Shariah Adherent Investors) in the SSM over two-year periods. The analysis follows the Markowitz portfolio selection model and incorporates regret aversion as an additional factor in the optimization process. Moreover, the analysis runs the simulations by focusing on three portfolio sizes (A = 15 stocks, B = 30 stocks, and C = 40 stocks). The optimization problem was addressed by generating 10,000 simulated investment portfolios that incorporated diverse regret perspectives and regret cases with varying levels[20]. This sub-section is divided into two parts. The first part examines the projected return distributions for the optimal portfolios (Maximum risk-adjusted return vs. minimum variance) and the impact of regret aversion on the portfolio construction process. Since the primary objective of this study is to examine the influence of regret on optimal portfolio allocation, the empirical analysis will focus on the findings related to the Maximum risk-adjusted return portfolio. The second part presents the optimal portfolio weights for various portfolio selection strategies based on three distinct optimization approaches (Classical Markowitz model with no regret, Markowitz model with regret against $U1$, and Markowitz model with regret against $U2$).

Statistical Characteristics of Anticipated Ex-ante Portfolio Returns

Tables C.1, C.3, C.5 and C.7 indicate the estimated return distributions for Strict Shariah-adherent Investors ($S1$), who only consider Pure stock classification as Shariah-compliant and treat other classifications as Non-Shariah-compliant, in both years under investigation. Tables C.1 and C.3 present the mean-variance ($\mu - \sigma$) portfolio's estimates, including the

[20] The relevant efficient frontier illustrations are included in the appendices.

portfolio mean return, standard deviation, Sharpe ratio, skewness[21], and expected shortfall at 5% and 1% levels. These computations are done for the entire SSM market with no Shariah constraints and regret considerations, Universe 1 (Shariah-complaint) with no regret, and both regret views assessed against Universe 1 (Shariah-complaint) as well as against Universe 2 (Non-Shariah-complaint). Tables C.5 and C.7 show the exact estimates related to the minimum-variance (Min-Var) optimal portfolios with the same regret views and cases. On the other hand, Tables C.2, C.4, C.6 and C.8 provide the estimated return distributions for Moderate Shariah-adherent Investors ($S2$), who consider both Pure and Mixed classifications as Shariah-compliant investments and treat the rest as Non-Shariah-compliant stocks in both study periods. While Tables C.2 and C.4 provide the $\mu - \sigma$ portfolios' estimates, Tables C.6 and C.8 show the estimates related to the Min-Var portfolios. Following the analysis of the classical Markowitz optimization approach without regret considerations, this paper presents and examines the results obtained by integrating regret sensitivity into the Markowitz portfolio optimization model. Basically, it examines the regret that may arise from the same investable universe ($U1$), as well as the regret stemming from the non-Shariah-compliant universe ($U2$). Both investment scenarios under consideration are assessed across these dimensions.

The analysis of the classical Markowitz optimization model for the $\mu - \sigma$ portfolios in the entire SSM market in 2018, presented in Table C.1, reveals that as the portfolio size increases from 15 to 40 stocks, the Sharpe ratio, a measure of risk-adjusted returns, improves, which indicating better diversification. However, this increase in diversification is accompanied by a slight decrease in mean returns, suggesting that larger portfolios provide more stable but slightly lower returns. Moreover, the negative skewness observed, particularly in Portfolios B and C, implies a greater likelihood of extreme negative returns as more stocks are included in the investment portfolio. Interestingly, the expected shortfall (ES), a metric of downside risk, is highest for the smaller Portfolio A, suggesting that smaller portfolios face greater potential losses in extreme scenarios. As for the Shariah-complaint universe ($U1$), the results show that the constraint of Shariah compliance imposes a performance penalty in traditional μ-σ terms, which as this paper anticipated. This is because a Shariah-adherent investor has a more limited set of investment options compared to a regular investor who can access the entire market. Compared to the results related to the classical Markowitz optimization model for the entire market, the Sharpe ratio of the Shariah-complaint Universe ($U1$) is lower than the full market case. This implies that restricting investments to Shariah-compliant stocks results

[21] In this empirical work, we analyze the skewness of portfolio expected returns, as it indicates the extent to which regret aversion influences investors to favour assets with positively skewed returns. These assets can reduce regret risk by increasing the likelihood of achieving returns closer to the ex-post best-performing investment alternative.

in a less optimal classical risk-return tradeoff under the traditional Markowitz framework. Additionally, the downside risk, as measured by ES, is slightly worse, reinforcing the idea that investing in Shariah-compliant stocks alone may not provide the best diversification benefits. Overall, investing in the SSM's full market provides better classical risk-adjusted returns compared to the Shariah-compliant universe ($U1$) when no regret is considered. In fact, the analysis indicates that investing solely in the $U1$ portfolio incurs an estimated opportunity cost ranging from 0.333 to 0.712 in terms of Sharpe ratio values. However, diversification was found to enhance classical risk-adjusted performance in both the Shariah-compliant and full market portfolios, with greater benefits observed in the case of the full market, as evidenced by the estimated opportunity cost.

Now let us consider the regret effect within the Shariah-compliant universe ($U1$) and observe how it may influence the optimal portfolios' estimates under both of the regret views. Here in this part of our analysis, we determine optimal portfolios under both return-regret and preference-regret for the average regret level or case ($\alpha = 0.5$) and the extreme regret level or case ($\alpha = 0.9$). Consistent with the approach outlined by Baule et al. (2019), the risk-aversion parameter (γ) is held constant at 3 for the $\mu - \sigma$ portfolio optimization, as the primary focus of this analysis is to assess the influence of regret sensitivity on the optimal portfolio allocation. In the following, this paper shows the results related to $S1$ (Strict Shariah-adherent Investors) and compares them to the findings related to $S2$ (Moderate Shariah-adherent Investors) for the two-year periods under study.

Under the return-regret view of $S1$ at an average regret level against the Shariah-complaint universe ($U1$), the mean return increases significantly (more than 20%) compared to the classical Markowitz approach. This indicates that incorporating regret aversion leads to a more aggressive asset allocation with higher potential returns. The higher standard deviation of these portfolios' returns confirms that the investor in this investment scenario ($S1$) is taking on more risk to pursue greater upside potential, in an effort to avoid future regret. Consequently, the Sharpe ratio decreases, suggesting a less favourable risk-return tradeoff relative to the classical Markowitz model. This is also reflected in the worsened expected shortfall measure, implying that the regret-aware portfolio is more vulnerable to potential losses. However, the positive skewness of the expected portfolio return implies a higher likelihood of extremely positive outcomes. As the investor's regret sensitivity increases toward the extreme regret level ($\alpha = 0.9$), the optimization results show the portfolios becoming highly speculative, with a sole focus on maximizing returns while disregarding risk considerations.

On the other hand, under the preference-regret view of $S1$ at an average regret level against the Shariah-complaint universe ($U1$), the mean returns are only slightly higher (almost by 1%) than the classical Markowitz approach, yet much lower than the return-regret model. However, in terms of risk, the standard deviation is significantly lower than the other two approaches. This suggests that investors in this case prioritize stability while minimizing their regret risk. This is reflected as well in the improved Sharpe ratio, indicating the investment portfolio is now better optimized for risk-adjusted returns. Furthermore, the expected portfolio returns exhibit better skewness scores compared to the classical Markowitz model, owing to the regret considerations in this approach. As for the downside risk, the expected shortfall remains similar to the classical model, indicating no significant increase due to incorporating regret. Even at an extreme regret level with $\alpha = 0.9$, both the mean returns and standard deviation increase but remain much lower than in the return-regret model. The expected portfolio returns are positively skewed due to the high regret sensitivity. Consequently, the expected shortfall is slightly worse than the classical model, yet still lower than the return-regret case.

Examining the results related to the regret from comparing to the uninvestable $U2$ (Non-Shariah-complaint Universe) under the return-focused view of investment scenario $S1$ at an average level of regret, the mean return rises sharply to nearly 100%, significantly exceeding the classical Markowitz portfolios of the entire market and Shariah-compliant investment portfolios. Additionally, the standard deviation increases to over 30%, indicating more aggressive and volatile investment portfolios. Consequently, the Sharpe ratio declines, suggesting diminished risk-adjusted performance. This is reflected in the intensified expected shortfall figures, which implies the increased downside risk due to the investment portfolios chasing the best-performing assets in the uninvestable universe ($U2$). However, the positive skewness of the expected return distribution suggests a greater chance of out-sized gains though the investment portfolios become highly speculative and unstable at a high regret sensitivity with α equals 0.9.

In contrast, under the preference-regret view of $S1$ at an average regret level against $U2$ (Non-Shariah-complaint Universe), the mean returns and standard deviation appear to be lower than those observed in the return-regret model. However, the Sharpe ratio is notably higher compared to the other models, although the skewness scores are not significantly different from the classical Markowitz model, suggesting some challenges in selecting investments with low volatility while satisfying regret constraints. Overall, the preference-regret model maintains a balanced approach even at extreme regret levels, potentially making it a suitable option for risk-aware Shariah-compliant investors.

Now, let us turn to Tables C.2 and C.6 which present the estimated return distribution for Moderate Shariah-adherent Investors' Portfolios ($S2$) in 2018. From Table C.2, it is clear that even though returns under the classical Markowitz model with no regret are lower for a moderate Shariah-adherent investor compared to an investor in the full market, the risk measures remain solid. This indicates that a moderate Shariah-adherent investor can still achieve good efficiency using the classical $\mu - \sigma$ tools though they may experience some performance gap or fear of missing out compared to the full market, as suggested by the Sharpe ratio values. In fact, the estimated Sharpe ratio opportunity cost of allocating solely to the $U1$ portfolio ranges from 0.324 to 0.404 points.

After accounting for the regret factor under the return-regret view of investment scenario $S2$ at an average regret level against the Shariah-complaint universe ($U1$), the mean return nearly doubled relative to the classical Markowitz model. However, this increase in expected return was accompanied by a substantial rise in portfolio risk, as evidenced by the standard deviation exceeding 24%. Despite the increased volatility, the Sharpe ratios remained strong although slightly lower than the classical Markowitz approach. Interestingly, the skewness scores flipped to the positive side, indicating the upside potential to achieve high returns due to the regret aversion factor. This suggests that the investor in this scenario is willing to accept greater risk exposure to mitigate the regret of potentially missing out on high-performing non-investable assets. However, as the regret sensitivity increases to the extreme level with α equals 0.9, the investment portfolios under this scenario may become more performance-driven and highly speculative reflecting a risk-heavy response to the fear of missing out.

On the other hand, under the preference-regret view of $S2$ at an average regret level against the Shariah-complaint universe ($U1$), the mean returns exceed the classical Markowitz approach while the standard deviation declines to be the lowest compared to the other models and cases. Consequently, this model achieves the highest Sharpe ratio values compared to the other approaches and cases though the skewness scores are below those observed in the return-regret model. Nevertheless, the skewness scores improve as the regret sensitivity increases to the extreme level although the investor must be willing to accept higher risk. In a nutshell, the investor in this scenario must balance their regret aversion with performance, aiming for what is realistically achievable while avoiding excessive risk.

Moving forward, under the return-focused regret view of investment scenario $S2$ with an average level of regret against the non-investable non-Shariah-complaint universe ($U2$), the optimization results reveal that the mean returns have increased significantly compared with the classical Markowitz model. However, the standard deviation has risen to a higher level than the regret considerations with $U1$. This suggests that an investor can achieve improved outcomes by solely accounting for regret from their investable list, as evidenced by the decline in Sharpe ratios. Consistent with the previous model that accounted for regret from $U1$, the portfolios' expected returns remain positively skewed, indicating the upside potential to attain high returns due to the regret aversion factor. In summary, the portfolios estimated using this model prioritize return maximization over risk considerations. They aggressively pursue the benchmark, sacrificing downside protection, particularly as the regret sensitivity increases to the extreme level.

The $S2$ preference-focused regret approach at an average regret level against the non-Shariah-complaint universe ($U2$) exhibits slightly improved mean returns compared to the classical model while their volatility decreases significantly. Consequently, the Sharpe ratios show a notable increase. Although the skewness scores remain negative, they are in better positions than the classical model, which does not account for the regret factor. Furthermore, the Expected Shortfall estimates indicate a much lower downside risk compared to the return-regret portfolios, nearly matching the classical model. This suggests that this view generates the most efficient portfolios, potentially making it the most appealing model and regret view for investors in the SSM.

To validate the robustness of our previous findings, this paper re-runs the portfolio optimization models using different stock investment lists and data from 2023. The optimization results show almost a similar trend to the 2018 findings, with the regret effect impacting the estimated portfolio return distributions for both investment scenarios although it is less significant in 2023 given the improvement of financial conditions observed during this year as discussed previously. Furthermore, the results indicate that as the Non-Shariah-compliant list becomes smaller, the potential regret factor diminishes. This might be due to the reduced likelihood of observing the highest return over an extended period as seen in the smaller investment opportunity set of the Non-Shariah-compliant universe ($U2$) for the moderate Shariah Adherent investment case.

To further support these findings, an additional analysis is conducted to examine the sensitivity of stock-level return distributions to varying degrees of regret aversion (see Figures C.1 to C.10). In the baseline case where the regret aversion coefficient (α) is set to zero, regret is not incorporated into the model, and the return distributions reflect only traditional risk. Under this condition, particularly in the preference-regret view (see Figures C.1 and C.6), the resulting distributions highlight the role of standard risk measures in portfolio construction without behavioural adjustments. As α increases from zero, the influence of regret aversion becomes progressively more pronounced, especially in models where regret is a central component of investor decision-making. Higher levels of α lead investors to perceive stocks as less attractive when compared to the ex-post best-performing alternatives, prompting the optimization framework to shift allocations toward portfolios that minimizes anticipated regret. This reinforces the value of regret-aware optimization, particularly in guiding asset selection under behavioural constraints. Accordingly, the regret-augmented Markowitz framework, especially under the preference-regret model, proves effective in identifying portfolios that strike a balance between expected performance and psychological comfort, while accommodating both traditional and regret-based risk dimensions across the two Shariah investment scenarios considered under study.

In conclusion, the key findings of this sub-section analysis demonstrate that the preference-regret model with average regret sensitivity ($\alpha = 0.5$) provides the most favourable balance between Shariah adherence, portfolio performance, and risk control for both investment scenarios. While return-regret models may appeal to investors seeking high absolute returns, they expose portfolios to excessive risk and instability. Therefore, it is recommended that both strict and moderate Shariah-adherent investors adopt a preference-regret approach to regret modeling prioritizing long-term stability and Shariah-principle coherence over short-term gains driven by benchmark-chasing behaviour. Additionally, this paper finds that as the non-Shariah list becomes smaller, the regret potential diminishes. This aligns with Baule et al. (2019)'s research, which indicates that changes to the investment opportunity set can potentially influence the risk of all assets. Thus, a well-defined specification of the investor's investment universe is particularly crucial in the regret model framework.

Optimal Allocation Process of Stocks with Regret-Based Considerations

This sub-section offers a comparative analysis of optimal portfolio allocations and stock characteristics derived from our diverse optimization models and investor preference specifications using two sets of complementary data tables. The first set outlines the top 10 optimal allocations for strict and moderate Shariah adherent estimated $\mu - \sigma$ portfolios in 2018 and 2023 (See Tables C.9, C.11, C.13 and C.15) while the second set highlights the descriptive statistics for the top allocated stocks under different investment scenarios and regret views (Refer to Tables C.10, C.12, C.14 and C.16). The former set details the asset compositions and weights of portfolios optimized using various classical and behavioural models whereas the latter set presents the statistical properties of the constituent stocks most frequently allocated across these models, capturing their mean returns, volatility, and distributional characteristics (e.g., skewness, kurtosis). This analytical framework facilitates a comprehensive comparison of how diverse investor behavioural assumptions and benchmark universes influence portfolio composition and asset selection process.

From the 2018 findings presented in Tables C.9 and C.11, portfolios constructed solely based on traditional risk-return trade-offs under $\mu - \sigma$ framework (Panel A), without incorporating any behavioural or regret considerations, exhibit diversified allocations with non-zero weights across 6 stocks, where the weight magnitudes gradually decline as the portfolio size increases. However, when the regret aversion factor with respect to foregone returns is incorporated, the portfolios shift toward more concentrated allocations. As the regret aversion coefficient (α) increases, investment weights converge sharply toward one or two assets, indicating that regret-minimizing investors under the return-regret view tend to favor past winners or high-performing stocks to minimize anticipated regret. In contrast, the allocations under the preference-regret view remain relatively diversified compared to return-regret portfolios though some concentration is observable as α increases. Notably, several of the same stocks (e.g. 4190, 4140, 4003, and 1120) appear consistently emphasizing their attractiveness across the three different utilized specifications. In Panel C, applying the same regret frameworks but evaluating regret against a non-Shariah-compliant universe to simulate the opportunity cost perceptions of Shariah-adherent investors, results in even more concentrated portfolio allocations. This is particularly evident under conditions of elevated regret aversion, as investors face intensified pressure to either match or surpass the performance of conventional benchmarks or to avoid underperforming relative to them.

After investigating certain stocks that appear more frequently than others across all models at the individual level from Tables C.10 and C.12, the analysis reveals that regret-augmented portfolio optimization models favour high-expected return stocks with positively skewed return distributions and negative excess kurtosis (e.g. 4140, 1120, and 4003). This is because positively skewed returns offer the potential for large gains while negative excess kurtosis implies thinner tails and a lower probability of extreme losses; thereby reducing the likelihood of painful regret. It makes sense that the regret-minimizing goal incorporated portfolio models would favour equities or stocks with these statistical characteristics.

The final phase of this analysis evaluates the results for the year 2023 to assess the robustness of the findings from 2018 (Refer to Tables C.13, C.14, C.15 and C.16). The analysis reveals a similar effect of regret on the optimal portfolio allocations as observed in 2018 though the impact is less significant this year, with optimal weights exhibiting less notable differentiation across the various models and approaches. Further investigation at the individual stock level indicates that the majority of the allocated stocks display high-expected returns with positively skewed return distributions and negative to zero excess kurtosis, confirming the improved financial conditions observed in the SSM during 2023.

Overall, the comparative analysis provided in this sub-section demonstrates how the use of different portfolio optimization models results in substantially divergent asset allocations, particularly when accounting for behavioural preferences and Shariah-compliance constraints. While the classical Markowitz model emphasizes diversification and mean-variance efficiency, regret-augmented models capture a more realistic psychological profile of investors, particularly their aversion to opportunity costs when adhering to Shariah principles. From a policy and practice standpoint, Shariah-compliant investors should consider integrating classical and behavioural portfolio optimization models. For instance, utilizing the preference-regret framework can help align financial performance with Shariah compliance principles and mitigate financial and regret risks associated with such constraints. Furthermore, understanding the statistical characteristics of frequently allocated assets provides valuable insights into portfolio resilience and potential vulnerability to tail risks.

4.5 Conclusion

The classical Markowitz mean-variance optimization framework remains a cornerstone of modern portfolio theory due to its practical and structured approach to determining optimal portfolio allocations. However, its core assumption—that investors are solely concerned with return and variance—limits its relevance for investors exhibiting psychological biases such as regret aversion. Those investors may not be fully satisfied with the classical Markowitz model, as it does not adequately capture their risk preferences. As a result, recent advancements have incorporated the psychological factor of regret aversion into the mean-variance portfolio optimization framework and have validated its effectiveness in addressing and resolving this issue.

Building on these recent research advancements, the present study applies a regret-sensitive portfolio optimization model to the context of Shariah-compliant investing in the SSM, using daily stock market data from two distinct time periods-2018 and 2023. This approach enables a quantitative evaluation of the psychological cost of regret that may arise when investors are limited to a religiously compliant investment universe. Such constraint can exclude potentially higher-return opportunities, resulting in measurable opportunity costs—both financial and psychological. By focusing on this dynamic, the study contributes to a relatively underexplored area of the literature, emphasizing the critical role of behavioural factors—particularly regret—in shaping investment decisions within Islamic financial markets.

A key contribution of this study is the development of a practical mathematical framework to support Shariah-adherent investors in aligning their portfolio strategies with their religious principles. The model evaluates two distinct investment scenarios reflecting varying levels of Shariah compliance. In the strict scenario, the investable universe is limited to Pure Shariah-compliant assets. In the moderate scenario, the universe is broadened to include both pure and mixed-compliant asset classes. For each case, the regret-sensitive optimization framework is applied to quantify the trade-offs between expected return, volatility, and psychological regret, both within the investable universe and in relation to the excluded non-compliant assets.

For the year 2018, the empirical evidence indicates that Strict Shariah-compliant investors incur a Sharpe ratio opportunity cost ranging from 0.333 to 0.712 points while Moderate Shariah-compliant investors face a smaller cost, ranging from 0.324 to 0.404 points. When regret aversion is incorporated into the portfolio optimization process, the results demonstrate that the preference-regret model, which balances expected returns with psychological costs of regret, provides a more robust and consistent approach to portfolio construction for both investor types. Although return-regret models may appeal to those seeking higher absolute returns, they often lead to increased volatility and greater divergence from both financial due diligence and Shariah compliance. In contrast, the preference-regret framework supports more stable, values-aligned investment decisions. Furthermore, the analysis finds that as the non-Shariah-compliant investment universe shrinks, the magnitude of potential regret also declines, emphasizing the importance of carefully defining the investable universe in any regret-sensitive modeling framework.

At the individual asset level, the study also reveals significant differences in optimal allocations depending on whether classical or regret-sensitive optimization models are used. Whereas the classical model emphasizes diversification and mean-variance efficiency, the regret-augmented models better reflect investor psychology—especially for those seeking to avoid the emotional cost of missed opportunities due to religious constraints. This result reinforces the importance of integrating behavioural preferences and ethical boundaries into portfolio decision frameworks.

To further validate the robustness of the findings, the study replicates the portfolio optimization analysis using an alternative set of stock investments and updated data from 2023. The results exhibit a trend broadly consistent with the 2018 analysis, confirming the influence of regret aversion on portfolio return distributions across both investment scenarios. However, the magnitude of the regret effect appears somewhat diminished in 2023, likely reflecting the relatively improved financial conditions observed during that period.

From a policy and practice standpoint, the findings highlight that Shariah-compliant investors, portfolio/fund managers, and investment institutions may benefit from combining classical optimization tools with behavioural extensions. For example, the proposed preference-regret model serves as a practical decision-making framework that aligns financial performance with ethical consistency, mitigating both financial and psychological risks. Moreover, the study's analysis of frequently selected assets provides useful insight into portfolio resilience and potential vulnerability to tail risks—factors critical to long-term investment success. This study suggests that managers of Shariah-compliant funds and portfolios should explicitly consider the role of regret—particularly the opportunity costs associated with excluding non-Shariah-compliant assets—when designing investment strategies and asset allocation frameworks. Accounting for this behavioural dimension can enhance decision-making under constraints and improve investor satisfaction over time.

One potential limitation of the study is its reliance on simulation to model regret aversion using real market data. To address this, the analysis includes robustness checks across different time periods, portfolio sizes, and individual stock-level allocations. Future research could further enhance these findings by empirically estimating regret sensitivity parameters from real investor behaviour—using surveys, experimental approaches, or portfolio data to capture revealed preferences directly. Such work would further deepen our understanding of how ethical and psychological factors jointly influence real-world investment decisions.

Chapter 5

Conclusions and Avenues for Future Research

This thesis comprises three research projects in the field of behavioural and financial economics. These academic studies shed new light on market participants' regret aversion, fear of missing out behaviour and the associated psychological and behavioural dimensions including market anomalies and biases. The first project investigates the disposition effect in the trading activities of two investor types—major brokerage accounts and local equity fund managers—in the SSM, focusing on two specific time periods: the Ramadan season and the COVID-19 pandemic. The second project provides a comparative analysis of herding behaviour between foreign and domestic investments in the SSM before and after its inclusion in the global EM indices. Finally, the third project utilizes the Markowitz regret optimization model to quantify the potential psychological costs of regret, which arise from an exclusive focus on Shariah-compliant investments and incorporates these opportunity costs into the portfolio optimization process.

The first research project investigates the presence of the disposition effect in the SSM and examines the behavioural trading patterns of two investor types: major brokerage and equity mutual fund investors during the holy month of Ramadan and the COVID-19 pandemic. This research project makes use of a novel dataset acquired from the CMA involving the daily trading records of the 20 most actively trading investors from each investor category in the SSM covering a period of three years spanning from January 2019 to December 2021. This research project's key findings, derived from the utilized statistical and regression techniques, are as follows. First, the project's initial part's findings reveal that, on average, major brokerage investors exhibit risk-averse tendencies and high sensitivity to stock price fluctuations. Interestingly, while the majority of these investors are not subject to the disposition effect, a significant portion (Around 30%) are found to not be exempt from this behavioural trading bias. Conversely, mutual fund managers are identified as more risk-seeking investors tending to realize greater losses while holding on to their gains. Second, although the statistical analyses suggest that major brokerage investors are inclined to realize an equal proportion of gains and losses, the regression results reveal that these investors respond asymmetrically to observed stock gains and losses, placing greater emphasis on avoiding the realization of losses though this relationship is found to be not statistically significant. In neutral market conditions with no significant gains or losses, major brokerage investors tend to realize around 90% of their stock positions. However, this proportion of realized positions decreases when they start observing stock gains and losses. For mutual fund investors, the study findings indicate that mutual fund investors exhibit a tendency to be driven primarily by their stock losses, as evidenced by both the statistical and regression analyses. Lastly, the research project proceeds then to examine the impact of two key events (Ramadan season and COVID-19 pandemic) on the disposition trading behaviour in the SSM. In the case of Ramadan, the regression model results showed that the Ramadan season does not have a statistically significant impact on the disposition trading behaviour of the two types of investors under the study. The results for the COVID-19 pandemic indicate that this event has a statistically significant impact on the disposition-driven trading of both investor groups—mutual funds and brokerage accounts. This research project acknowledges two limitations. First, the analysis is constrained to the observable trades due to the unavailability of comprehensive investor stock holding data. Second, the findings reflect the trading behaviour of the most actively traded brokerage accounts and mutual funds, and may not necessarily be representative of the entire trading segments within the SSM. To address these limitations, this research project emphasizes the need for enhanced disclosure of investor-level data including average cost prices, stock holding positions and demographic characteristics. Such information would enable a more comprehensive assessment of the disposition effect within the SSM and facilitate a deeper understanding of how the study's major events impact this trading behaviour.

Next, the second research project extends the thesis's investigation by examining the impact of Tadawul's inclusion in global EM indices on herding behaviour in the SSM. The project constructs three investment portfolios, based on the market data of SSM-listed stocks prior to the inclusion, representing overall market investments, investments in which QFI is involved and exclusive local investments. The empirical work is organized into two main steps. First, it explores the presence of herding behaviour across all the constructed portfolios and during the specified time periods (The full study period, along with the sub-periods preceding and following the inclusion) employing the methodologies used in Christie and Huang (1995) and Chang et al. (2000). Second, the study analyzes the characteristics of the observed herding behaviour within the investment portfolios during the designated time frames relying on an established empirical approach by Galariotis et al. (2015). This research project presents key findings derived from the regression analyses performed in both steps. In the first step, the regression findings reveal consistent herding behaviour in the SSM, observed both before and after its inclusion in the global EM indices. This herd mentality tendency is particularly prevalent among local investors although the intensity varies across different market conditions and investment portfolios. Notably, the herding behaviour for the stocks associated with QFI's investments becomes statistically insignificant during the sub-period following the inclusion except when the market is experiencing a declining trend. In the second step, the regression findings indicate that the observed herding tendencies in the SSM can largely be attributed to intentional herding behaviour. However, local investors have exhibited a propensity for engaging in a form of spurious or unintentional herding under various market conditions, particularly during periods of market decline in the sub-period following the inclusion. In fact, the study findings imply that following the market's inclusion in global EM indices, the intentional herding behaviour exhibited among the stocks associated with QFI's investments becomes statistically insignificant. However, the intentional herding behaviour remains statistically significant for stocks involving only local investment trades during the same period. This research project acknowledges the limitations in evaluating herding behaviour in the SSM and analyzing the impact of the market's inclusion in global EM indices. The key challenge lies in distinguishing investments by QFI from those of local investors since local investors continue to trade the same stocks as QFIs both before and after the inclusion. To address this, the study conducts estimations on stocks not included as part of QFI investments and accessible only to local investors, in addition to dividing the study period into two sub-periods before and after QFI entry. For future research, the incorporation of an investor attention index constructed using data from the internet and social media channels could provide an alternative means to capture and account for spurious herding behaviour within the empirical regression model.

As the final component of this academic thesis, the last research project provides a practical mathematical model, based on the previous empirical model presented by Baule et al. (2019), to assist Shariah-compliant investors in aligning their investment strategies with their religious principles. This proposed mathematical framework quantitatively evaluates the psychological and financial costs of regret associated with a focus on Shariah-compliant investments. In fact, this framework effectively accounts for higher-order return properties, including skewness and kurtosis, which are not adequately captured by the traditional Markowitz model. Consequently, investors who display a tendency toward loss aversion or regret aversion may find the regret-augmented models more satisfactory than the traditional model, as the former better captures their risk preferences. In this research's investigation settings, the study design assumes that there are two distinct non-overlapping investment domains including investable Shariah-compliant and uninvestable non-Shariah-compliant assets, within the overall SSM's market universe. Additionally, the research project investigates two different investment scenarios (Strict and Moderate Shariah Adherent) arising from the differing Shariah-compliant categorizations. The first investment scenario restricts investors to a limited set of Pure Shariah-compliant stocks, within which they must construct optimal portfolios. In contrast, the second scenario grants investors greater flexibility, enabling them to select from a broader pool of Shariah-compliant stocks covering two distinct classifications: Pure and Mixed stocks. This research utilizes daily market data for all listed stocks on the SSM over the 2018 and 2023 fiscal years. The findings of this research project, derived from the 2018 optimization model analyses, indicate that strict Shariah-compliant investors face a Sharpe ratio opportunity cost ranging from 0.333 to 0.712 points whereas moderate Shariah-compliant investors incur a lower cost, between 0.324 and 0.404 points. At the point when factoring in regret aversion into the optimization process, the study's findings conclude that the preference-regret model that takes into account average regret aversion offers an optimal trade-off between Shariah compliance, portfolio performance and risk management across the two investment scenarios investigated. The findings of this research project also indicate that as the range of non-Shariah-compliant investment options becomes more limited, investors are less likely to experience regret. Therefore, this study highlights the critical need for a well-defined specification of the investor's investment universe within the regret model framework. This is essential to accurately assess the potential for regret and determine the optimal portfolio allocations that align with the investor's risk preferences. Then, this research project further enriches its empirical analysis by undertaking a comparative assessment of the optimal allocation process at the individual stock level. The findings demonstrate that the utilization of diverse portfolio optimization models leads to substantially varied asset allocations, particularly when accounting for behavioural preferences and Shariah-compliance constraints. While the traditional Markowitz model emphasizes diversification benefits and mean-variance optimization techniques, regret-augmented models better capture the psychological inclinations of investors including their aversion to incurring opportunity costs when adhering to Shariah-compliant investment principles. These findings are further validated using 2023 data, which confirm similar trends to 2018 though the impact of regret aversion is less significant due to more favourable market conditions seen during this year. Finally, this research project recognizes a potential limitation in its reliance on a simulation-based approach using real market data. To address this, the study conducts various levels of investigation including running the optimization models across different time periods, considering portfolios of varying sizes and analyzing the optimal allocations at the individual stock level. These robust checks aim to validate the models' findings in a comprehensive and detailed manner. In terms of future works, this research believes that subsequent studies may seek to investigate and quantify the regret sensitivity levels of Shariah-compliant investors in order to capture their revealed preferences associated with regret aversion behaviour. Researchers could determine risk aversion and regret sensitivity parameters by observing real-time investment decisions and portfolio allocations, potentially utilizing survey methods or techniques from experimental economics.

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Appendix A

An Appendix Chapter Related to Disposition Effect Investigation

Table A.1: Retail Brokerage Accounts Sample Representativeness

Date	Retail's Total Buy Value Traded*	Retail's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Panel A. Main Market				
Jan 2019	28,515.9	30,538.8	10.8%	9.8%
Feb 2019	20,048.7	21,055.2	12.5%	11.4%
Mar 2019	25,420.0	26,868.6	10.5%	10.2%
Apr 2019	26,890.7	28,881.7	10.6%	10.1%
May 2019	23,657.4	25,256.8	15.0%	14.8%
Jun 2019	20,902.5	21,949.7	11.6%	11.8%
Jul 2019	23,176.2	25,572.5	12.5%	10.1%
Aug 2019	16,169.9	16,346.9	15.0%	16.8%
Sep 2019	21,152.0	24,172.0	14.0%	13.2%
Oct 2019	23,528.7	24,971.1	11.2%	9.6%
Nov 2019	21,939.1	23,243.6	10.9%	9.9%
Dec 2019	41,488.8	47,925.9	9.2%	7.9%
Jan 2020	40,274.1	41,959.8	9.2%	8.7%
Feb 2020	31,586.4	33,115.8	7.2%	7.8%
Mar 2020	53,868.4	49,769.0	8.0%	9.4%
Apr 2020	52,040.2	50,112.6	6.5%	6.6%
May 2020	35,644.7	35,501.3	6.3%	6.6%
Jun 2020	64,590.3	66,989.3	5.8%	5.6%
Jul 2020	67,813.8	68,751.2	5.2%	5.1%
Aug 2020	88,768.2	90,171.5	5.4%	5.1%
Sep 2020	166,881.7	166,475.9	5.4%	5.4%
Oct 2020	142,693.6	144,752.6	5.5%	5.4%
Nov 2020	168,230.4	168,652.3	5.6%	5.5%
Dec 2020	164,393.3	167,194.4	6.1%	5.9%
Jan 2021	100,030.2	101,791.2	7.1%	7.1%
Feb 2021	152,793.6	153,825.4	8.0%	7.8%
Mar 2021	172,762.5	172,567.3	7.9%	8.0%
Apr 2021	98,424.3	99,929.8	9.6%	9.4%
May 2021	82,618.8	81,617.8	9.0%	8.7%
Jun 2021	163,164.0	161,884.2	9.4%	9.4%
Jul 2021	76,120.6	74,291.6	8.6%	8.8%
Aug 2021	75,272.2	74,742.0	8.2%	8.1%
Sep 2021	71,352.9	72,217.9	8.4%	8.1%
Oct 2021	73,912.5	72,078.1	10.3%	10.7%
Nov 2021	58,782.9	56,784.8	9.0%	10.0%
Dec 2021	72,379.2	74,059.4	7.7%	7.6%
Descriptive Statistics	Mean		9.0%	8.8%
	Max		15.0%	16.8%
	Min		5.2%	5.1%
	Std Dev		2.7%	2.6%
Panel B. Nomu - Parallel Market				
Jan 2019	35.1	35.9	-	-
Feb 2019	52.6	51.5	1.7%	1.7%
Mar 2019	31.1	29.1	0.0%	0.1%
Apr 2019	24.7	26.1	-	-
May 2019	21.7	23.4	-	-
Jun 2019	48.2	44.3	0.1%	0.1%
Jul 2019	0.7	2.0	4.0%	1.4%
Aug 2019	18.9	18.8	-	-
Sep 2019	27.5	26.6	0.1%	0.1%
Oct 2019	155.5	134.1	2.7%	2.9%
Nov 2019	1,247.7	1,188.9	6.1%	6.3%
Dec 2019	361.0	355.9	8.9%	9.1%
Jan 2020	266.2	256.7	6.9%	7.2%
Feb 2020	338.3	329.3	6.4%	6.2%
Mar 2020	365.8	366.3	4.2%	4.4%
Apr 2020	660.0	658.1	10.8%	10.3%
May 2020	396.3	390.2	5.7%	6.3%
Jun 2020	655.2	641.3	5.5%	5.7%
Jul 2020	297.9	298.6	1.9%	2.0%
Aug 2020	325.5	322.1	2.0%	1.6%
Sep 2020	926.7	895.6	2.1%	2.3%
Oct 2020	792.0	766.7	1.3%	1.2%
Nov 2020	905.8	891.4	2.1%	2.4%
Dec 2020	978.1	973.6	1.9%	2.0%
Jan 2021	968.0	980.1	1.6%	1.6%
Feb 2021	991.7	1,001.2	1.6%	1.5%
Mar 2021	592.1	633.6	1.0%	1.1%
Apr 2021	269.8	282.1	-	-
May 2021	672.1	643.4	2.5%	2.7%
Jun 2021	1,004.1	660.3	1.1%	1.6%
Jul 2021	411.7	403.6	6.3%	6.1%
Aug 2021	710.8	687.4	6.5%	5.3%
Sep 2021	1,206.5	1,189.6	6.0%	5.9%
Oct 2021	624.1	628.1	4.2%	2.9%
Nov 2021	1,276.3	900.3	3.1%	2.2%
Dec 2021	1,727.8	1,696.0	7.7%	7.5%
Descriptive Statistics	Mean		3.8%	3.6%
	Max		10.8%	10.3%
	Min		0.0%	0.1%
	Std Dev		2.7%	2.7%

* All values are presented in million Saudi Riyals. Source: Capital Market Authority (CMA), Saudi Stock Exchange (Tadawul)

Table A.2: Mutual Funds Sample Representativeness

Panel A. Main Market					
Date		MF's Total Buy Value Traded*	MF's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Jan 2019		1,596.2	1,760.2	53.3%	60.6%
Feb 2019		894.7	3,492.0	44.2%	18.9%
Mar 2019		1,907.4	2,522.4	65.4%	46.8%
Apr 2019		3,234.6	3,531.3	64.6%	64.3%
May 2019		2,745.9	3,977.8	63.8%	55.9%
Jun 2019		1,334.9	2,795.1	53.8%	40.1%
Jul 2019		1,689.8	2,161.1	57.5%	59.1%
Aug 2019		1,640.6	2,290.9	68.4%	54.2%
Sep 2019		1,941.8	2,272.1	53.7%	54.0%
Oct 2019		2,417.5	2,684.8	41.7%	38.3%
Nov 2019		1,544.6	3,250.4	35.9%	42.7%
Dec 2019		5,318.8	5,330.2	51.4%	33.6%
Jan 2020		4,663.9	3,391.6	23.9%	41.0%
Feb 2020		3,563.6	3,277.8	22.2%	37.1%
Mar 2020		4,055.5	5,611.7	37.3%	48.9%
Apr 2020		2,437.7	2,013.7	18.2%	43.0%
May 2020		2,641.9	2,725.7	46.2%	35.8%
Jun 2020		1,582.7	1,942.2	52.5%	48.4%
Jul 2020		1,577.0	1,692.5	54.1%	57.8%
Aug 2020		2,000.3	1,779.0	51.5%	51.4%
Sep 2020		3,842.6	2,968.5	32.0%	47.0%
Oct 2020		2,160.7	2,301.0	62.2%	58.9%
Nov 2020		2,449.6	4,254.5	63.2%	33.0%
Dec 2020		3,223.3	2,968.9	66.9%	46.1%
Jan 2021		1,990.7	3,436.0	68.5%	39.1%
Feb 2021		2,367.8	2,394.0	61.2%	64.3%
Mar 2021		5,840.9	4,433.2	23.8%	52.8%
Apr 2021		9,681.4	6,377.1	16.1%	30.3%
May 2021		3,921.6	4,648.7	21.3%	56.3%
Jun 2021		5,445.9	5,399.7	58.9%	67.5%
Jul 2021		2,588.9	2,752.6	61.7%	68.5%
Aug 2021		2,980.3	3,752.1	51.2%	54.4%
Sep 2021		3,652.5	3,903.8	38.8%	58.2%
Oct 2021		3,384.8	5,117.0	58.7%	55.5%
Nov 2021		3,418.7	4,609.0	39.3%	50.4%
Dec 2021		3,062.7	4,270.9	53.9%	54.5%
Descriptive Statistics - Main Market	Mean			48.3%	49.1%
	Max			68.5%	68.5%
	Min			16.1%	18.9%
	Std Dev			15.4%	11.1%

Panel B. Nomu - Parallel Market					
Date		Institution's Total Buy Value Traded*	Institution's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Jan 2019		1.5	1.1	-	-
Feb 2019		2.6	4.4	-	-
Mar 2019		0.6	3.0	-	-
Apr 2019		0.7	1.4	-	4.8%
May 2019		0.9	1.1	-	29.9%
Jun 2019		0.4	0.1	-	-
Jul 2019		82.7	78.3	-	-
Aug 2019		0.5	0.8	-	-
Sep 2019		1.1	0.4	-	-
Oct 2019		2.5	3.7	-	-
Nov 2019		49.9	42.6	72.4%	55.6%
Dec 2019		1.6	1.4	-	-
Jan 2020		0.2	0.2	-	-
Feb 2020		0.6	0.5	-	-
Mar 2020		0.4	0.6	-	-
Apr 2020		0.3	0.0	-	-
May 2020		0.1	0.3	-	-
Jun 2020		1.0	0.9	-	-
Jul 2020		1.6	0.2	-	-
Aug 2020		0.2	0.4	-	-
Sep 2020		5.3	0.9	-	-
Oct 2020		1.5	0.2	-	-
Nov 2020		1.4	0.9	-	-
Dec 2020		2.4	0.2	-	-
Jan 2021		8.1	1.4	-	-
Feb 2021		4.8	0.9	-	-
Mar 2021		39.5	1.8	-	-
Apr 2021		12.2	1.0	-	-
May 2021		3.8	0.0	-	-
Jun 2021		8.4	10.3	86.6%	-
Jul 2021		8.7	2.2	26.5%	-
Aug 2021		15.1	3.2	66.2%	-
Sep 2021		10.8	21.7	-	17.7%
Oct 2021		6.3	7.6	-	-
Nov 2021		18.0	4.2	-	-
Dec 2021		122.8	65.7	-	-
Descriptive Statistics - Nomu - Parallel Market	Mean			62.9%	27.0%
	Max			86.6%	55.6%
	Min			26.5%	4.8%
	Std Dev			22.3%	18.7%

* All values are presented in million Saudi Riyals. Source: Capital Market Authority (CMA), Saudi Stock Exchange (Tadawul)

Table A.3: Retail Sample Representativeness (Only Traceable Trades Included)

Date	Retail's Total Buy Value Traded*	Retail's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Panel A. Main Market				
Jan 2019	28,515.9	30,538.8	6.8%	5.9%
Feb 2019	20,048.7	21,055.2	6.9%	6.6%
Mar 2019	25,420.0	26,868.6	6.4%	5.9%
Apr 2019	26,890.7	28,881.7	6.2%	5.6%
May 2019	23,657.4	25,256.8	7.2%	7.1%
Jun 2019	20,902.5	21,949.7	5.1%	4.8%
Jul 2019	23,176.2	25,572.5	6.7%	10.1%
Aug 2019	16,169.9	16,346.9	6.6%	6.8%
Sep 2019	21,152.0	24,172.0	5.8%	5.0%
Oct 2019	23,528.7	24,971.1	5.3%	4.5%
Nov 2019	21,939.1	23,243.6	4.7%	4.3%
Dec 2019	41,488.8	47,925.9	3.7%	3.1%
Jan 2020	40,274.1	41,959.8	4.6%	4.5%
Feb 2020	31,586.4	33,115.8	4.1%	4.2%
Mar 2020	53,868.4	49,769.0	3.6%	3.8%
Apr 2020	52,040.2	50,112.6	3.6%	3.6%
May 2020	35,644.7	35,501.3	3.0%	3.1%
Jun 2020	64,590.3	66,989.3	3.8%	3.5%
Jul 2020	67,813.8	68,751.2	3.9%	3.7%
Aug 2020	88,768.2	90,171.5	3.9%	3.7%
Sep 2020	166,881.7	166,475.9	4.3%	4.2%
Oct 2020	142,693.6	144,752.6	4.5%	4.4%
Nov 2020	168,230.4	168,652.3	4.7%	4.6%
Dec 2020	164,393.3	167,194.4	5.2%	5.1%
Jan 2021	100,030.2	101,791.2	6.4%	6.4%
Feb 2021	152,793.6	153,825.4	7.3%	7.1%
Mar 2021	172,762.5	172,567.3	7.1%	7.1%
Apr 2021	98,424.3	99,929.8	8.1%	7.9%
May 2021	82,618.8	81,617.8	7.7%	7.4%
Jun 2021	163,164.0	161,884.2	7.9%	8.0%
Jul 2021	76,120.6	74,291.6	7.7%	7.7%
Aug 2021	75,272.2	74,742.0	6.2%	6.0%
Sep 2021	71,352.9	72,217.9	6.8%	6.7%
Oct 2021	73,912.5	72,078.1	7.1%	7.6%
Nov 2021	58,782.9	56,784.8	7.0%	7.4%
Dec 2021	72,379.2	74,059.4	6.3%	6.1%
Descriptive Statistics	Mean		5.7%	5.5%
	Max		8.1%	8.0%
	Min		3.0%	3.1%
	Std Dev		1.5%	1.5%
Panel B. Nomu - Parallel Market				
Jan 2019	35.1	35.9	-	-
Feb 2019	52.6	51.5	1.7%	1.7%
Mar 2019	31.1	29.1	0.0%	0.1%
Apr 2019	24.7	26.1	-	-
May 2019	21.7	23.4	-	-
Jun 2019	48.2	44.3	0.1%	0.1%
Jul 2019	0.7	2.0	4.0%	1.4%
Aug 2019	18.9	18.8	-	-
Sep 2019	27.5	26.6	0.1%	0.1%
Oct 2019	155.5	134.1	2.7%	2.9%
Nov 2019	1,247.7	1,188.9	6.1%	6.3%
Dec 2019	361.0	355.9	8.9%	9.1%
Jan 2020	266.2	256.7	6.9%	7.2%
Feb 2020	338.3	329.3	6.4%	6.2%
Mar 2020	365.8	366.3	4.2%	4.4%
Apr 2020	660.0	658.1	10.3%	10.3%
May 2020	396.3	390.2	5.7%	5.6%
Jun 2020	655.2	641.3	5.4%	5.7%
Jul 2020	297.9	298.6	1.7%	1.7%
Aug 2020	325.5	322.1	1.8%	1.4%
Sep 2020	926.7	895.6	2.1%	2.3%
Oct 2020	792.0	766.7	1.3%	1.2%
Nov 2020	905.8	891.4	2.1%	2.4%
Dec 2020	978.1	973.6	1.9%	2.0%
Jan 2021	968.0	980.1	1.3%	1.3%
Feb 2021	991.7	1,001.2	1.6%	1.5%
Mar 2021	592.1	633.6	1.0%	1.1%
Apr 2021	269.8	282.1	-	-
May 2021	672.1	643.4	2.5%	2.7%
Jun 2021	1,004.1	660.3	1.1%	1.6%
Jul 2021	411.7	403.6	6.3%	6.1%
Aug 2021	710.8	687.4	6.5%	5.3%
Sep 2021	1,206.5	1,189.6	5.4%	5.3%
Oct 2021	624.1	628.1	4.2%	2.9%
Nov 2021	1,276.3	900.3	3.0%	2.0%
Dec 2021	1,727.8	1,696.0	7.7%	7.5%
Descriptive Statistics	Mean		3.7%	3.5%
	Max		10.3%	10.3%
	Min		0.0%	0.1%
	Std Dev		2.7%	2.7%

* All values are presented in million Saudi Riyals. Source: Capital Market Authority (CMA), Saudi Stock Exchange (Tadawul).

Table A.4: Funds Sample Representativeness (Only Traceable Trades Included)

Panel A. Main Market

Date	MF's Total Buy Value Traded*	MF's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Jan 2019	1,596.2	1,760.2	15.6%	1.3%
Feb 2019	894.7	3,492.0	17.5%	0.8%
Mar 2019	1,907.4	2,522.4	24.6%	2.9%
Apr 2019	3,234.6	3,531.3	39.5%	2.6%
May 2019	2,745.9	3,977.8	18.5%	5.2%
Jun 2019	1,334.9	2,795.1	21.8%	3.5%
Jul 2019	1,689.8	2,161.1	22.4%	8.9%
Aug 2019	1,640.6	2,290.9	29.9%	5.0%
Sep 2019	1,941.8	2,272.1	34.6%	8.2%
Oct 2019	2,417.5	2,684.8	24.3%	12.1%
Nov 2019	1,544.6	3,250.4	19.9%	12.1%
Dec 2019	5,318.8	5,330.2	29.9%	9.4%
Jan 2020	4,663.9	3,391.6	19.0%	17.3%
Feb 2020	3,563.6	3,277.8	17.2%	10.7%
Mar 2020	4,055.5	5,611.7	22.5%	19.4%
Apr 2020	2,437.7	2,013.7	10.5%	24.7%
May 2020	2,641.9	2,725.7	16.9%	25.5%
Jun 2020	1,582.7	1,942.2	37.5%	29.1%
Jul 2020	1,577.0	1,692.5	42.6%	27.3%
Aug 2020	2,000.3	1,779.0	34.6%	26.6%
Sep 2020	3,842.6	2,968.5	19.4%	23.5%
Oct 2020	2,160.7	2,301.0	46.6%	28.1%
Nov 2020	2,449.6	4,254.5	46.1%	16.6%
Dec 2020	3,223.3	2,968.9	47.7%	24.8%
Jan 2021	1,990.7	3,436.0	40.2%	24.8%
Feb 2021	2,367.8	2,394.0	33.0%	36.1%
Mar 2021	5,840.9	4,433.2	15.3%	29.6%
Apr 2021	9,681.4	6,377.1	10.5%	18.0%
May 2021	3,921.6	4,648.7	17.3%	26.9%
Jun 2021	5,445.9	5,399.7	46.2%	24.8%
Jul 2021	2,588.9	2,752.6	43.2%	32.3%
Aug 2021	2,980.3	3,752.1	26.6%	33.1%
Sep 2021	3,652.5	3,903.8	19.0%	35.5%
Oct 2021	3,384.8	5,117.0	28.5%	21.8%
Nov 2021	3,418.7	4,609.0	18.7%	15.7%
Dec 2021	3,062.7	4,270.9	20.8%	17.8%
Descriptive Statistics - Main Market	Mean		27.2%	18.4%
	Max		47.7%	36.1%
	Min		10.5%	0.8%
	Std Dev		11.0%	10.4%

Panel B. Nomu - Parallel Market

Date	Institution's Total Buy Value Traded*	Institution's Total Sell Value Traded*	Sample Representative (Buy)	Sample Representative (Sell)
Jan 2019	1.5	1.1	-	-
Feb 2019	2.6	4.4	-	-
Mar 2019	0.6	3.0	-	-
Apr 2019	0.7	1.4	-	-
May 2019	0.9	1.1	-	-
Jun 2019	0.4	0.1	-	-
Jul 2019	82.7	78.3	-	-
Aug 2019	0.5	0.8	-	-
Sep 2019	1.1	0.4	-	-
Oct 2019	2.5	3.7	-	-
Nov 2019	49.9	42.6	72.4%	55.6%
Dec 2019	1.6	1.4	-	-
Jan 2020	0.2	0.2	-	-
Feb 2020	0.6	0.5	-	-
Mar 2020	0.4	0.6	-	-
Apr 2020	0.3	0.0	-	-
May 2020	0.1	0.3	-	-
Jun 2020	1.0	0.9	-	-
Jul 2020	1.6	0.2	-	-
Aug 2020	0.2	0.4	-	-
Sep 2020	5.3	0.9	-	-
Oct 2020	1.5	0.2	-	-
Nov 2020	1.4	0.9	-	-
Dec 2020	2.4	0.2	-	-
Jan 2021	8.1	1.4	-	-
Feb 2021	4.8	0.9	-	-
Mar 2021	39.5	1.8	-	-
Apr 2021	12.2	1.0	-	-
May 2021	3.8	0.0	-	-
Jun 2021	8.4	10.3	86.6%	-
Jul 2021	8.7	2.2	26.5%	-
Aug 2021	15.1	3.2	66.2%	-
Sep 2021	10.8	21.7	-	-
Oct 2021	6.3	7.6	-	-
Nov 2021	18.0	4.2	-	-
Dec 2021	122.8	65.7	-	-
Descriptive Statistics - Nomu - Parallel Market	Mean		62.9%	55.6%
	Max		86.6%	55.6%
	Min		26.5%	-
	Std Dev		22.3%	0%

* All values are presented in million Saudi Riyals. Source: Capital Market Authority (CMA), Saudi Stock Exchange (Tadawul).

Table A.5: The GICS Structure of Stock Market Sectors

GICS codes	Industry Group
4010	Banks
2010	Capital Goods
2020	Commercial & Professional Svc
2520	Consumer Durables & Apparel
2530	Consumer Services
4020	Diversified Financials
1010	Energy
3020	Food & Beverages
3010	Food & Staples Retailing
3510	Health Care Equipment & Svc
4030	Insurance
1510	Materials
5020	Media
3520	Pharma, Biotech & Life Science
40401010	Real Estate Investment Trust
40401020	Real Estate Mgmt & Development
2550	Retailing
4510	Software & Services
5010	Telecommunication Services
2030	Transportation
5510	Utilities

Source: MSCI, Guiding Principles and Methodology for GICS - March 2023.

Table A.6: Marginal & Joint Probability Distribution For Brokerage Stock Gains

Sell	$x \leq 1\%$	$1\% < x \leq 9\%$	$9\% < x \leq 20\%$	$20\% < x \leq 40\%$	$40\% < x \leq 60\%$	$60\% < x \leq 100\%$	$x > 100\%$	Total
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1	71.07%	27.42%	1.02%	0.32%	0.10%	0.04%	0.03%	100.00%
Total	71.07%	27.42%	1.02%	0.32%	0.10%	0.04%	0.03%	100.00%

Notes: This table shows the probability distribution for brokerage accounts' stock gains where $n = 41,997$ and $x = stockreturn$.

Table A.7: Marginal & Joint Probability Distribution For Brokerage Stock Losses

Sell	$x \leq -1\%$	$-1\% < x \leq -10\%$	$-10\% < x \leq -20\%$	$-20\% < x \leq -40\%$	$x > -40\%$	Total
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1	81.32%	18.04%	0.46%	0.15%	0.02%	100.00%
Total	81.32%	18.04%	0.46%	0.15%	0.02%	100.00%

Notes: This table shows the probability distribution for brokerage accounts' stock losses where $n = 34,971$ and $x = stockreturn$.

Table A.8: Marginal & Joint Probability Distribution For Mutual Fund Stock Gains

Sell	$x \leq 1\%$	$1\% < x \leq 9\%$	$9\% < x \leq 20\%$	$20\% < x \leq 40\%$	$40\% < x \leq 60\%$	$60\% < x \leq 100\%$	$x > 100\%$	Total
0	11.54%	24.98%	6.26%	2.67%	0.69%	0.17%	0.00%	46.31%
1	3.33%	16.90%	12.49%	13.22%	4.53%	2.39%	0.83%	53.69%
Total	14.87%	41.88%	18.75%	15.89%	5.22%	2.56%	0.83%	100.00%

Notes: This table shows the probability distribution for Mutual Funds' stock gains where $n = 10,469$ and $x = stockreturn$.

Table A.9: Marginal & Joint Probability Distribution For Mutual Fund Stock Losses

Sell	$x \leq -1\%$	$-1\% < x \leq -10\%$	$-10\% < x \leq -20\%$	$-20\% < x \leq -40\%$	$x > -40\%$	Total
0	18.21%	27.47%	3.52%	0.75%	0.00%	49.96%
1	5.28%	26.83%	9.41%	7.93%	0.60%	50.04%
Total	23.50%	54.30%	12.93%	8.68%	0.60%	100.00%

Notes: This table shows the probability distribution for Mutual Funds' stock losses where $n = 4,656$ and $x = stockreturn$.

Table A.10: PGR, PLR and the Disposition Ratio for Brokerage Accounts After Excluding the Outliers

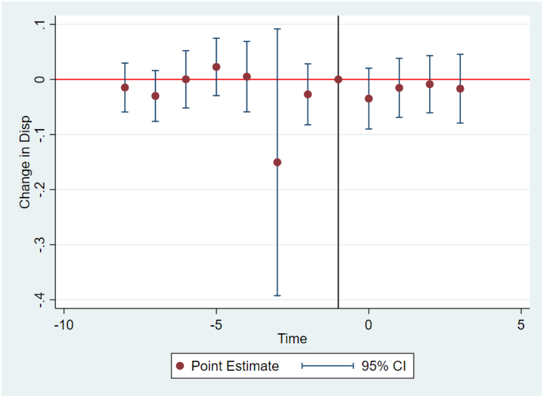
	Full Year	December	Jan.-Nov.
Panel A. At Aggregate Level			
$\mu_{(PGR)}$	0.91058	0.91356	0.91025
$\mu_{(PLR)}$	0.91146	0.91156	0.91145
Diff in Prop.	-.00089	0.00201	-.00121
$DISP-Ratio$	0.99903	1.00220	0.99868
t-statistics	-0.5524	0.3986	-0.7119
P-value (Diff in Prop.>0)	0.710	0.345	0.762
Obs.	77663	7632	70031
Panel B. At Account Level			
$\mu_{(PGR)}$	0.84137	0.82049	0.84281
$\mu_{(PLR)}$	0.84836	0.84580	0.84927
Diff in Prop.	-0.00699	-0.02531	-0.00646
$DISP-Ratio$	0.99176	0.97007	0.99239
t-statistics	-0.2507	-0.1937	-0.22325
P-value (Diff in Prop.>0)	0.43726	0.540	0.421
Obs.	77663	7632	70031

Notes. This table compares the overall Proportion of Gains Realized (PGR) to the overall Proportion of Losses Realized (PLR) across the brokerage accounts after excluding the outliers and across time (2019–2021). The *t*-statistics evaluate the null hypothesis (H_0), which states that the mean proportional differences are equal to zero under the premise that all realized gains, paper gains, realized losses, and paper losses are the consequence of separate choices.

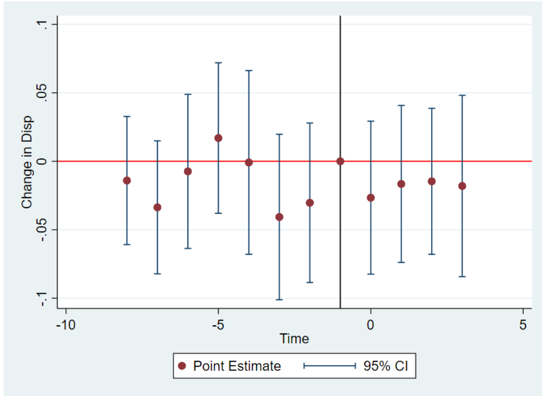
Table A.11: Difference in Means for COVID-19 pandemic's Leads and Lags

	(a) Brokerage Accounts - Overall				(b) Brokerage Accounts - Outliers Excluded				(c) Mutual Funds			
Lead/Lag	DISP	*t*-statistic	DISP-Ratio	Obs.	DISP	*t*-statistic	DISP-Ratio	Obs.	DISP	*t*-statistic	DISP-Ratio	Obs.
-12	0.00	0.00	1.00	429	0.01	0.29	1.01	424	-0.00	-0.37	0.93	148
-11	-0.03	-1.40	0.97	387	-0.03	-1.45	0.97	385	0.01	0.07	1.01	97
-10	-0.05	-2.91	0.94	449	-0.05	-2.78	0.95	442	-0.14	-2.27	0.70	131
-9	-0.03	-1.49	0.96	453	-0.03	-1.52	0.96	452	-0.23	-3.21	0.54	97
-8	0.03	1.62	1.04	396	0.03	1.31	1.03	393	-0.11	-1.49	0.81	129
-7	-0.01	-0.48	0.99	345	-0.03	-1.13	0.97	332	0.08	1.06	1.24	89
-6	-0.03	-1.56	0.96	455	-0.03	-1.33	0.97	447	0.01	0.08	1.02	88
-5	-0.03	-1.12	0.97	330	-0.03	-1.14	0.97	325	-0.30	-3.84	0.52	135
-4	-0.06	-2.63	0.93	461	-0.06	-2.78	0.93	455	-0.06	-0.87	0.88	138
-3	0.01	0.45	1.01	493	0.01	0.34	1.01	491	-0.14	-2.46	0.68	153
-2	0.04	1.68	1.05	421	0.04	1.68	1.05	421	-0.24	-4.75	0.54	172
-1	-0.01	-0.58	0.99	502	-0.01	-0.58	0.99	502	-0.09	-1.82	0.76	197
0	-0.05	-2.43	0.94	513	-0.06	-2.51	0.93	501	-0.15	-2.87	0.69	194
1	-0.01	-0.18	0.99	465	-0.02	-0.80	0.98	454	-0.12	-1.47	0.72	147
2	0.06	2.53	1.07	547	0.06	2.89	1.07	529	0.10	1.69	1.55	167
3	0.01	0.46	1.01	534	0.00	-0.15	1.00	518	-0.35	-4.80	0.47	188
4	-0.02	-0.72	0.98	359	-0.02	-1.09	1.00	349	-0.09	-1.49	0.76	147
5	-0.01	-0.55	0.99	582	-0.01	-0.42	0.99	570	-0.06	-1.27	0.82	197
6	0.00	0.10	1.00	533	0.00	0.18	1.00	520	-0.00	-0.05	0.99	226
7	-0.03	-1.32	0.97	520	-0.03	-1.43	0.97	500	-0.11	-2.51	0.71	200
8	-0.04	-2.60	0.95	632	-0.03	-2.12	0.96	599	0.01	0.18	1.04	144
9	0.00	-0.02	1.00	601	-0.00	-0.11	1.00	578	-0.05	-1.22	0.78	156
10	-0.01	-0.29	0.99	630	0.00	0.01	1.00	601	0.09	0.89	1.33	55
11	-0.03	-1.69	0.96	663	-0.02	-1.01	0.98	632	-0.05	-0.66	0.83	87
12	-0.00	-0.18	1.00	624	-0.00	-0.24	0.99	576	-0.24	-3.41	0.59	138
13	0.03	2.00	1.04	637	0.01	0.74	1.01	600	-0.02	-0.25	0.92	57
14	-0.04	-2.00	0.96	773	-0.04	-2.80	0.95	727	-0.17	-2.20	0.67	103
15	-0.07	-3.12	0.92	651	-0.06	-2.94	0.93	614	0.29	2.46	3.00	30
16	-0.07	-3.02	0.91	563	-0.06	-2.61	0.94	521	-0.12	-1.65	0.75	112
17	-0.08	-3.89	0.91	738	-0.05	-2.96	0.94	687	-0.27	-2.01	0.49	35
18	-0.05	-2.65	0.94	465	-0.03	-1.88	0.96	443	0.09	0.83	1.23	77
19	-0.01	-0.53	0.99	592	-0.00	-0.05	1.00	551	-0.05	-0.16	0.92	11
20	-0.04	-1.70	0.94	583	-0.07	-3.10	0.92	538	0.36	-	3.56	9
21	-0.07	-2.77	0.92	558	-0.06	-2.73	0.93	506	0.08	0.47	1.22	25
22	0.04	1.48	1.05	510	0.02	0.91	1.02	459	-0.18	-1.13	0.71	28
23	0.03	1.27	1.03	600	0.00	0.06	1.00	551	-0.08	-0.63	0.83	43

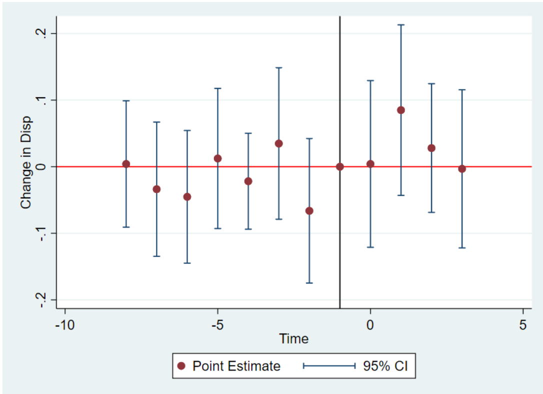
Notes. This table shows the mean differences between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR) for the leads and lags of COVID-19 pandemic event. The *t*-statistics evaluate the null hypothesis (H_0), which states that the proportional differences are equal to zero under the assumption that all realized gains, paper gains, realized losses, and paper losses of a brokerage investor are the consequence of separate choices.



(a) Brokerage Account *DISP* - Overall



(b) Brokerage Account *DISP* - Outliers Excluded



(c) Mutual Fund *DISP*

Figure A.1: Impacts of Ramadan Season on Investors' Disposition Trading Behaviour Measured by *DISP*

*Notes.*This figure shows event time coefficients estimated from equation (2.6) for all brokerage accounts, after excluding outliers from the brokerage account sample, and all mutual funds. Point estimates are presented along with their 95% CIs. The baseline period is one month before the event (Ramadan).

Table A.12: Difference in Means for COVID-19 Pandemic's Restrictions Period

(a) Brokerage Accounts - Overall

Lead/Lag	DISP	*t*-statistic	DISP-Ratio	Obs.
Before	-0.020	-3.285	0.977	5,419
During	0.010	1.028	1.012	2,520
After	-0.024	-4.849	0.972	11,055

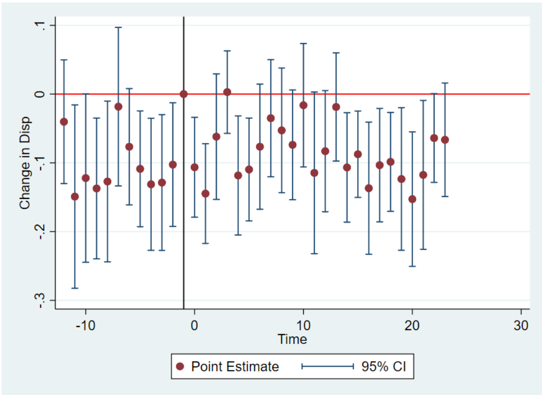
(b) BA - Outliers Excluded

DISP	*t*-statistic	DISP-Ratio	Obs.
-0.020	-3.306	0.977	5,361
0.003	0.366	1.004	2,452
-0.023	-5.238	0.974	10,380

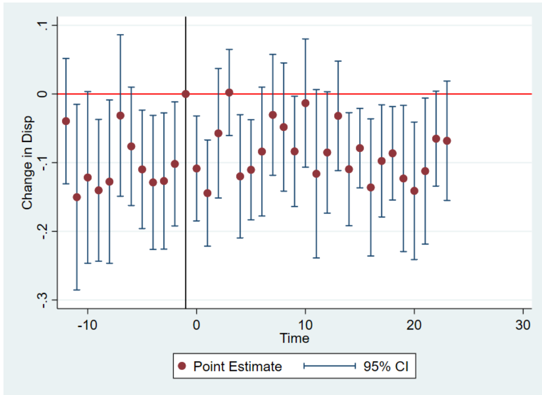
(c) Mutual Funds

	DISP	*t*-statistic	DISP-Ratio	Obs.
Before	-0.023	-0.843	0.938	726
During	-0.093	-2.843	0.790	491
After	-0.081	-6.042	0.791	2,933

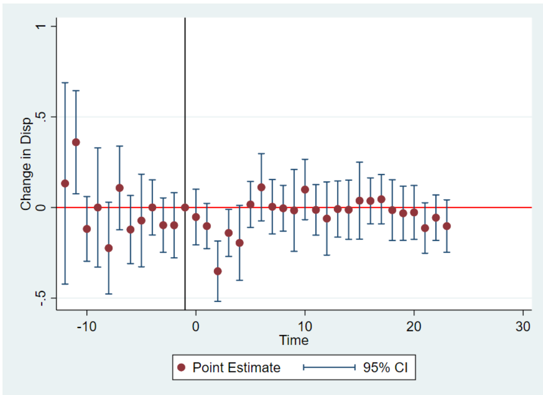
Notes. This table shows the mean differences between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR) for the COVID-19 Pandemic's Restrictions Period (Before/During/After). The *t*-statistics evaluate the null hypothesis (H_0), which states that the proportional differences are equal to zero under the assumption that all realized gains, paper gains, realized losses, and paper losses of a brokerage investor are the consequence of separate choices.



(a) Brokerage Account *DISP* - Overall



(b) Brokerage Account *DISP* - Outliers Excluded



(c) Mutual Fund *DISP*

Figure A.2: Impacts of COVID-19 on Investors' Disposition Trading Behaviour Measured by *DISP*

*Notes.*This figure shows event time coefficients estimated from equation (2.6) for all brokerage accounts, after excluding outliers from the brokerage account sample, and all mutual funds. Point estimates are presented along with their 95% CIs. The baseline period is one month before the event (COVID-19).

Table A.13: Complete Stock Liquidation Across Brokerage Accounts in the SSM

Portfolio	Complete liquidated Stocks	Share of Complete liquidation
A	212	100.0%
B	165	100.0%
C	220	99.1%
D	200	100.0%
E	211	100.0%
F	67	90.5%
G	177	100.0%
H	181	100.0%
I	172	99.4%
J	224	100.0%
K	33	86.8%
L	110	100.0%
M	189	99.5%
N	129	100.0%
O	92	100.0%
P	20	80.0%
Q	202	100.0%
R	183	100.0%
S	87	97.8%
T	199	100.0%
Avg.	**154**	**97.7%**

Note: This table summarizes the number and percentage share of completely liquidated stocks across 20 retail brokerage portfolios from the Saudi stock market. For each portfolio, the "Complete Liquidated Stocks" column lists the count of stocks fully sold, while the "Share of Complete Liquidation" column shows the proportion of the portfolio's traceable holdings that were fully liquidated. Most portfolios have a complete liquidation rate near or at 100%, with an overall average of 154 fully liquidated stocks per portfolio and a mean liquidation share of 97.7%.

Table A.14: Complete Stock Liquidation Across Mutual Funds in the SSM

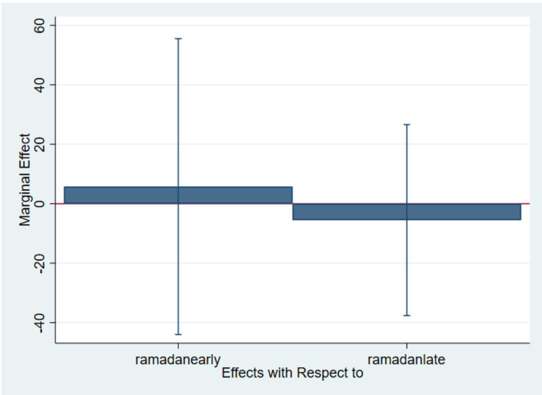
Fund	Complete liquidated Stocks	Share of Complete liquidation
A	25	83.3%
B	23	67.6%
C	44	95.7%
D	20	95.2%
E	132	100.0%
F	9	45.0%
G	25	67.6%
H	48	80.0%
I	22	75.9%
J	39	88.6%
K	14	66.7%
L	32	82.1%
M	23	88.5%
N	36	87.8%
O	4	66.7%
P	47	83.9%
Q	54	91.5%
R	71	97.3%
S	28	84.8%
T	26	96.3%
Avg.	**36**	**82.2%**

Note: This table presents the number and percentage share of completely liquidated stocks across 20 local equity mutual funds in the Saudi stock market. The "Complete Liquidated Stocks" column shows the count of stocks entirely sold from each fund, while the "Share of Complete Liquidation" column indicates the proportion of the fund's traceable holdings that were fully liquidated. Liquidation rates vary from 45% to 100%, with an average of 36 fully liquidated stocks per fund and a mean liquidation share of 82.2%.

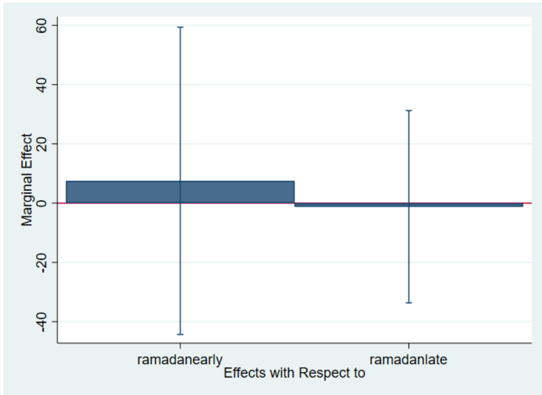
Table A.15: PGR, PLR, and Disposition Ratios Across Brokerage Accounts and Mutual Funds – Month-End Trading Analysis by Calendar Type

	Full Year	Islamic Calendar (1)	Islamic Calendar (2)	Gregorian Calendar
Panel A. Brokerage Accounts				
PGR	0.90259	0.89331	0.89420	0.89968
PLR	0.90334	0.90837	0.91038	0.90602
Diff in Proportions	-0.00075	-0.01505	-0.01618	-0.00634
DISP-Ratio	0.99917	0.98343	0.98223	0.99300
t-statistics	-0.4453	-1.9511	-2.0682	-0.7414
P-value (Diff in Prop. >0)	0.672	0.974	0.981	0.771
Obs.	78813	3,895	3,711	3,042
Panel B. Mutual Funds				
PGR	0.29751	0.29327	0.31672	0.30818
PLR	0.43773	0.39165	0.39829	0.42549
Diff in Proportions	-0.1402	-0.0984	-0.0816	-0.1173
DISP-Ratio	0.67967	0.74880	0.79520	0.72430
t-statistics	-15.6442	-2.6687	-2.0671	-3.0977
P-value (Diff in Prop. >0)	0.999	0.996	0.980	0.999
Obs.	7985	478	412	406

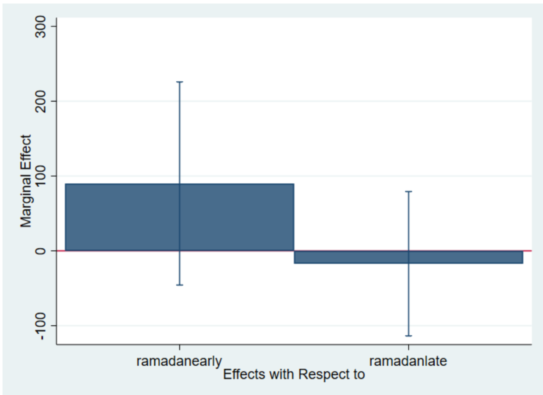
Notes. This table presents the overall Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR), along with the resulting Disposition Ratio (PGR/PLR), for all brokerage accounts and mutual funds in the dataset from 2019 to 2021. The analysis is conducted for the last trading day of each month, based on both Islamic and Gregorian calendars. Two variants of the Islamic calendar analysis are shown: (1) includes trading days during Ramadan, while (2) excludes them. The table reports the difference in proportions (PGR – PLR), the corresponding t-statistics, and p-values testing the null hypothesis (H) that the mean difference in proportions is zero with the assumption that realized gains/losses and unrealized gains/losses result from separate investor decisions.



(a) Marginal Effect with *Account, Trans. & Time FE* - Overall



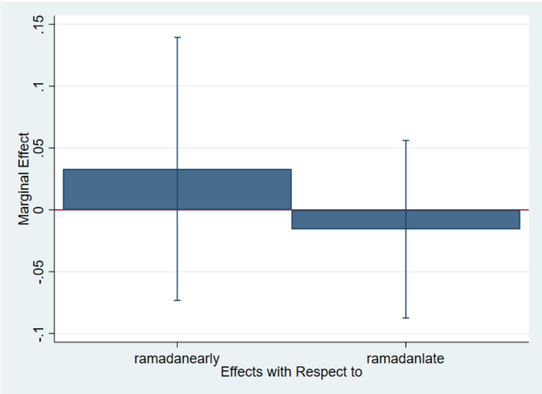
(b) Marginal Effect with *Account, Trans. & Time FE* - Outliers Excluded



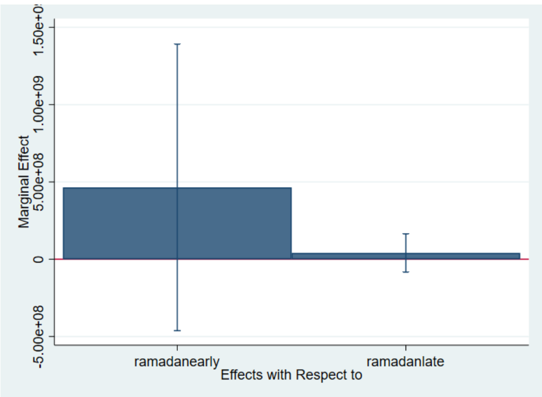
(c) Marginal Effect with *Fund, Trans. & Time FE*

Figure A.3: Marginal Effects of Early and Late Ramadan Periods on the $DISP-Ratio$ for Brokerage Accounts and Mutual Fund Managers

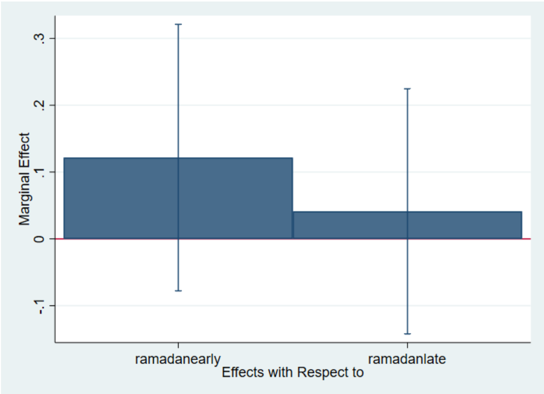
Notes. Estimates are derived from fixed-effects panel regressions, controlling for investor-specific unobserved heterogeneity and clustering standard errors at the investor transactional level. The "Ramadan Early" period corresponds to the first five trading days of Ramadan; the "Ramadan Late" period corresponds to the last five trading days. Point estimates are shown with 95% confidence intervals, and the horizontal red line denotes the baseline effect (non-Ramadan trading days). Panels show results for: (a) brokerage accounts in the full sample (top left), (b) brokerage accounts excluding outliers (top right), and (c) mutual fund managers (bottom).



(a) Marginal Effect with *Account, Trans. & Time FE* - Overall



(b) Marginal Effect with *Account, Trans. & Time FE* - Outliers Excluded



(c) Marginal Effect with *Fund, Trans. & Time FE*

Figure A.4: Marginal Effects of Early and Late Ramadan Periods on the $DISP$ for Brokerage Accounts and Mutual Fund Managers

Notes. Estimates are derived from fixed-effects panel regressions, controlling for investor-specific unobserved heterogeneity and clustering standard errors at the investor transactional level. The "Ramadan Early" period corresponds to the first five trading days of Ramadan; the "Ramadan Late" period corresponds to the last five trading days. Point estimates are shown with 95% confidence intervals, and the horizontal red line denotes the baseline effect (non-Ramadan trading days). Panels show results for: (a) brokerage accounts in the full sample (top left), (b) brokerage accounts excluding outliers (top right), and (c) mutual fund managers (bottom).

Appendix B

An Appendix Chapter Related to Herding Mentality Investigation

Table B.1: Regression Results of Daily Fundamental Driven $CSAD_t$ and Non-fundamental Driven $CSAD_t$ on Portfolio Returns Over Full Sample Period for Whole, Up, and Down Market Conditions

Portfolio	Whole Market Conditions			Down Market Conditions			Up Market Conditions		
	γ_1	γ_2	R^2	γ_1^D	γ_2^D	R^2	γ_1^U	γ_2^U	R^2
Panel A: Fundamental Driven $CSAD_t$									
Overall Investment Portfolio	0.012	0.009***	0.203	0.106***	-0.002	0.648	-0.069***	0.002*	0.162
	(1.22)	(3.99)		(16.24)	(-1.56)		(-9.31)	(1.91)	
Portfolio with QFI Investments	0.040***	-0.001	0.077	0.076***	-0.005**	0.232	0.011	-0.006***	0.015
	(4.90)	(-0.62)		(7.39)	(-2.07)		(1.51)	(-4.52)	
Portfolio of Domestic Investments	-0.003	0.009***	0.194	0.083***	-0.001	0.568	-0.062***	0.0002	0.077
	(-0.42)	(5.69)		(12.02)	(-1.01)		(-9.16)	(0.08)	
Panel B: Non-fundamental Driven $CSAD_t$									
Overall Investment Portfolio	0.350***	-0.019***	0.480	0.284***	-0.010***	0.565	0.420***	-0.021***	0.461
	(23.07)	(-6.30)		(13.81)	(-2.58)		(22.28)	(-6.54)	
Portfolio with QFI Investments	0.255***	-0.005*	0.406	0.236***	-0.003	0.500	0.275***	-0.005	0.330
	(17.05)	(-1.71)		(11.35)	(-0.67)		(13.77)	(-1.22)	
Portfolio of Domestic Investments	0.419***	-0.025***	0.533	0.352***	-0.016***	0.615	0.487***	-0.027***	0.512
	(27.61)	(-9.49)		(16.34)	(-4.49)		(24.63)	(-6.82)	

Notes. The table displays the calculated coefficients of the regression models specified in (3.10) and (3.11), offering a comprehensive overview of the correlation between the Daily $CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ with $R_{p,t}$. The daily $CSAD_{NONFUND,t} = \epsilon_t$ and is extracted from the regression model specified in equation (3.8). Then, the daily $CSAD_{FUND,t}$ is computed as specified in (3.9). The data covers the entire sample period from 01/09/2014 to 25/01/2024. This study conducts these calculations on three distinct investment portfolios, each with its own unique composition. The first portfolio includes the overall market portfolio, comprising 193 stocks listed before 2019. From this pool of 193 stocks, the second portfolio focuses on 86 stocks representing approximately 99% of QFI investment opportunities in the SSM and are part of MSCI IMI constituents, while the final constructed portfolio comprises the remaining set of 107 stocks representing investments exclusive to local traders. The findings are generated by using the sample in various market conditions, including overall, down-market, and up-market scenarios. The regression's standard errors are robust, with t-statistics shown in parentheses. *, ** and *** denote that the coefficients are significant at the 10%, 5% and 1% levels, respectively.

(a) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

(b) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Portfolio with QFI Investments

(c) $CSAD_{FUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

(d) $CSAD_{NONFUND,t}$ and $R_{p,t}$ Relationship in the Dedicated Portfolio for Domestic Investments

Figure B.1: The Relationship between the Daily Fundamental Driven $CSAD_t$ and Non-fundamental Driven $CSAD_t$ with the Corresponding Equally Weighted Investment Portfolio Return ($R_{p,t}$) over the Full Sample Period

Table B.2: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over Full Sample Period and across Market Conditions for Large Companies Listed in the SSM

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.800*** (81.25)	0.324*** (18.59)	-0.016*** (-3.76)	0.392	0.778*** (60.17)	0.332*** (15.11)	-0.011** (-2.81)	0.469	0.814*** (56.38)	0.350*** (12.96)	-0.026*** (-3.41)	0.317	2,348	1.25	3.03*
Portfolio with QFI Investments	0.773*** (73.69)	0.313*** (17.97)	-0.017*** (-4.51)	0.336	0.771*** (49.96)	0.281*** (11.80)	-0.011** (-2.24)	0.367	0.768*** (53.30)	0.356*** (14.06)	-0.026*** (-4.52)	0.312	2,348	4.62**	4.17**
Portfolio of Domestic Investments	0.751*** (47.21)	0.454*** (15.80)	-0.028*** (-3.81)	0.367	0.738*** (38.93)	0.367*** (12.62)	-0.009* (-1.75)	0.427	0.748*** (39.28)	0.576*** (20.10)	-0.063*** (-10.05)	0.345	2,348	26.33***	43.02***

Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for large companies listed in the SSM over the period from 01/09/2014 to 25/01/2024. Results are presented for three portfolios: the overall investment portfolio of large-cap stocks listed before 2019, a QFI investment portfolio of large-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining large-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%).

Table B.3: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over Full Sample Period and across Market Conditions for Small and Medium Companies Listed in the SSM

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.878***	0.366***	-0.010***	0.624	0.858***	0.390***	-0.012***	0.727	0.890***	0.361***	-0.018***	0.432	2,348	1.10	1.25
	(104.16)	(24.45)	(-3.02)		(67.55)	(17.99)	(-2.84)		(86.27)	(20.68)	(-4.92)				
Portfolio with QFI Investments	0.773***	0.313***	-0.017***	0.336	0.771***	0.281***	-0.011**	0.367	0.768***	0.356***	-0.026***	0.312	2,348	4.62**	4.17**
	(73.69)	(17.97)	(-4.51)		(49.96)	(11.80)	(-2.24)		(53.30)	(14.06)	(-4.52)				
Portfolio of Domestic Investments	0.847***	0.412***	-0.017***	0.614	0.825***	0.420***	-0.017***	0.695	0.855***	0.430***	-0.027***	0.477	2,348	0.13	3.64*
	(88.67)	(27.83)	(-6.22)		(56.25)	(19.33)	(-4.79)		(70.94)	(22.59)	(-6.58)				

Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for small and medium companies listed in the SSM over the period from 01/09/2014 to 25/01/2024. Results are presented for three portfolios: the overall investment portfolio of small and medium-cap stocks listed before 2019, a QFI investment portfolio of small and medium-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining small and medium-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%).

Table B.4: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period Before SSM Inclusion and across Market Conditions for Large Companies Listed in the SSM

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.772*** (44.45)	0.333*** (10.51)	-0.017** (-2.07)	0.422	0.763*** (39.72)	0.272*** (8.41)	-0.002 (-0.03)	0.514	0.788*** (33.97)	0.381*** (11.41)	-0.033*** (-4.87)	0.348	1,081	5.51**	10.48***
Portfolio with QFI Investments (1)	0.732*** (43.73)	0.347*** (13.15)	-0.021*** (-3.54)	0.392	0.741*** (29.77)	0.279*** (7.66)	-0.005 (-0.62)	0.419	0.727*** (35.21)	0.407*** (13.11)	-0.035*** (-7.27)	0.386	1,081	7.24***	10.76***
Portfolio of Domestic Investments	0.787*** (28.39)	0.355*** (6.89)	-0.019 (-1.41)	0.306	0.777*** (26.01)	0.243*** (4.98)	-0.009 (-0.85)	0.409	0.813*** (27.31)	0.450*** (11.47)	-0.050*** (-7.30)	0.252	1,081	11.05***	21.51***

Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for large companies listed in the SSM over the period before the SSM inclusion in the EM indices, spanning from 01/09/2014 to 31/12/2018. Results are presented for three portfolios: the overall investment portfolio of large-cap stocks listed before 2019, a QFI investment portfolio of large-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining large-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%). (1) Please note that this period does not include QFI investments since their inflows started after the inclusion in the EM indices, which took place in the year 2019. The underlying stocks of this portfolio are only traded by local investors during this period (from 01/09/2014 to 31/12/2018).

Table B.5: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period Before SSM Inclusion and across Market Conditions for Small and Medium Companies Listed in the SSM

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.833*** (72.37)	0.378*** (20.30)	-0.008** (-2.01)	0.732	0.830*** (47.05)	0.384*** (13.86)	-0.007 (-1.42)	0.811	0.830*** (58.70)	0.396*** (18.47)	-0.019*** (-6.01)	0.552	1,081	0.11	3.94**
Portfolio with QFI Investments (1)	0.793*** (64.76)	0.347*** (17.82)	-0.007* (-1.79)	0.634	0.789*** (44.49)	0.336*** (12.08)	-0.004 (-0.70)	0.728	0.791*** (47.61)	0.371*** (14.48)	-0.016*** (-3.99)	0.486	1,081	0.90	3.65*
Portfolio of Domestic Investments	0.842*** (59.94)	0.394*** (21.01)	-0.012*** (-3.94)	0.703	0.833*** (38.03)	0.400*** (14.34)	-0.012*** (-2.95)	0.760	0.843*** (49.76)	0.409*** (18.26)	-0.021*** (-5.58)	0.570	1,081	0.06	2.09

Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for small and medium companies listed in the SSM over the period after the SSM inclusion in the EM indices, spanning from 01/01/2019 to 25/01/2024. Results are presented for three portfolios: the overall investment portfolio of small and medium-cap stocks listed before 2019, a QFI investment portfolio of small and medium-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining small and medium-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%). (1) Please note that this period does not include QFI investments since their inflows started after the inclusion in the EM indices, which took place in the year 2019. The underlying stocks of this portfolio are only traded by local investors during this period (from 01/09/2014 to 31/12/2018).

Table B.6: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period After SSM Inclusion and across Market Conditions for Large Companies Listed in the SSM

Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.820***	0.322***	-0.015***	0.364	0.798***	0.337***	-0.017***	0.435	0.843***	0.291***	-0.005***	0.289	1,267	1.35	3.81*
	(69.19)	(15.88)	(-4.37)		(45.67)	(12.46)	(-4.48)		(52.37)	(10.12)	(-0.94)				
Portfolio with QFI Investments	0.807***	0.281***	-0.013***	0.275	0.806***	0.265***	-0.012**	0.313	0.811***	0.276***	-0.004	0.246	1,267	0.07	1.12
	(60.07)	(12.00)	(-2.93)		(43.31)	(8.95)	(-2.43)		(42.85)	(8.43)	(-0.61)				
Portfolio of Domestic Investments	0.708***	0.560***	-0.034***	0.452	0.699***	0.490***	-0.024***	0.477	0.703***	0.645***	-0.051***	0.446	1,267	8.69***	5.43**
	(40.65)	(21.43)	(-8.29)		(27.66)	(13.14)	(-4.45)		(29.82)	(17.37)	(-4.99)				

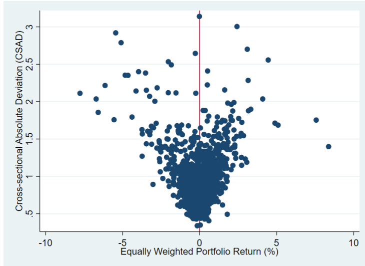
Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for large companies listed in the SSM over the period after the SSM inclusion in the EM indices, spanning from 01/01/2019 to 25/01/2024. Results are presented for three portfolios: the overall investment portfolio of large-cap stocks listed before 2019, a QFI investment portfolio of large-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining large-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%).

Table B.7: Regression Results of Daily $CSAD_t$ on $R_{p,t}$ Over the Period After SSM Inclusion and across Market Conditions for Small and Medium Companies Listed in the SSM

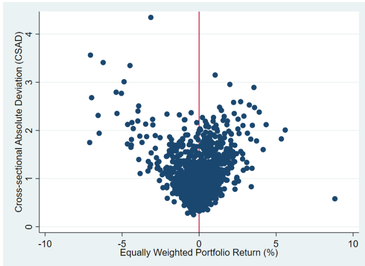
Portfolio	Whole Market Conditions				Down Market Conditions				Up Market Conditions				Obs.	Wald test statistics	
	α	γ_1	γ_2	R^2	α^D	γ_1^D	γ_2^D	R^2	α^U	γ_1^U	γ_2^U	R^2		$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Overall Investment Portfolio	0.908*** (78.04)	0.370*** (17.55)	-0.019*** (-4.66)	0.475	0.881*** (50.31)	0.406*** (13.31)	-0.022*** (-4.39)	0.592	0.926*** (61.97)	0.358*** (13.01)	-0.029*** (-5.35)	0.316	1,267	1.37	0.81
Portfolio with QFI Investments	0.959*** (77.30)	0.254*** (11.41)	-0.005 (-1.17)	0.314	0.911*** (53.02)	0.309*** (9.91)	-0.011** (-2.10)	0.486	0.998*** (58.05)	0.207*** (6.93)	-0.005 (-0.89)	0.142	1,267	5.55**	0.70
Portfolio of Domestic Investments	0.843*** (64.64)	0.448*** (20.31)	-0.028*** (-7.29)	0.500	0.814*** (40.75)	0.452*** (13.84)	-0.027*** (-5.28)	0.588	0.844*** (48.17)	0.499*** (15.74)	-0.050*** (-8.11)	0.403	1,267	1.07	8.59***

Notes. This table reports regression estimates from equations (5), (6), and (7), examining the relationship between the Daily CSAD and portfolio returns for small and medium companies listed in the SSM over the period after the SSM inclusion in the EM indices, spanning from 01/01/2019 to 25/01/2024. Results are presented for three portfolios: the overall investment portfolio of small and medium-cap stocks listed before 2019, a QFI investment portfolio of small and medium-cap listed stocks included in MSCI IMI constituents, and a domestic investment portfolio of the remaining small and medium-cap listed stocks primarily traded by local traders. Regressions are estimated under whole, down-market, and up-market conditions, with coefficients (α, γ_1, γ_2), R^2 values, and robust t-statistics (in parentheses) reported. The regression's standard errors are robust for heteroskedasticity and autocorrelation and Wald χ^2 statistics test the null hypotheses $\gamma_1^D = \gamma_1^U$ and $\gamma_2^D = \gamma_2^U$. Statistical significance is denoted by *** (1%), ** (5%), and * (10%).

(a) The Relationship in the Overall Investment Portfolio

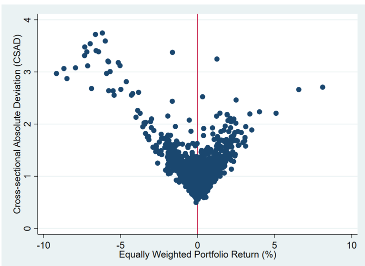


(b) The Relationship in the Portfolio with QFI Investments

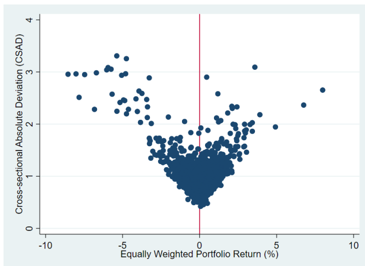


(c) The Relationship in the Dedicated Portfolio for Domestic Investments

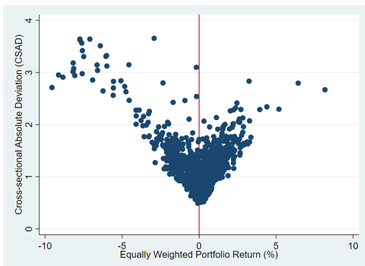
Figure B.2: The Relationship between Daily Cross-Sectional Absolute Deviation ($CSAD_t$) and Equally Weighted Large-Cap Portfolio Returns ($R_{p,t}$) Prior to the Inclusion of the SSM



(a) The Relationship in the Overall Investment Portfolio

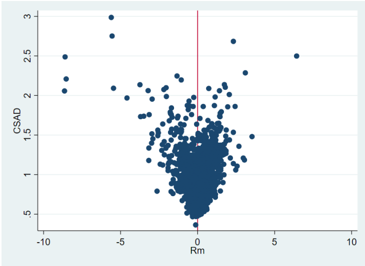


(b) The Relationship in the Portfolio with QFI Investments

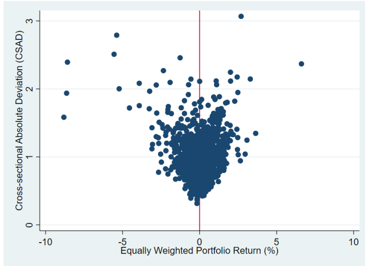


(c) The Relationship in the Dedicated Portfolio for Domestic Investments

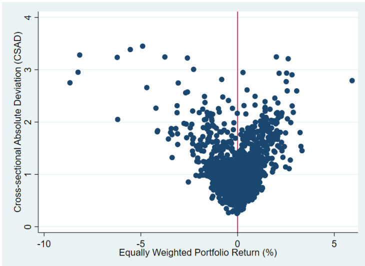
Figure B.3: The Relationship between Daily Cross-Sectional Absolute Deviation ($CSAD_t$) and Equally Weighted Small and Medium-Cap Portfolio Returns ($R_{p,t}$) Prior to the Inclusion of the SSM



(a) The Relationship in the Overall Investment Portfolio



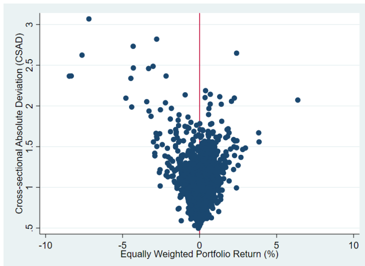
(b) The Relationship in the Portfolio with QFI Investments



(c) The Relationship in the Dedicated Portfolio for Domestic Investments

Figure B.4: The Relationship between Daily Cross-Sectional Absolute Deviation ($CSAD_t$) and Equally Weighted Large-Cap Portfolio Returns ($R_{p,t}$) Following the Inclusion of the SSM

(a) The Relationship in the Overall Investment Portfolio



(b) The Relationship in the Portfolio with QFI Investments

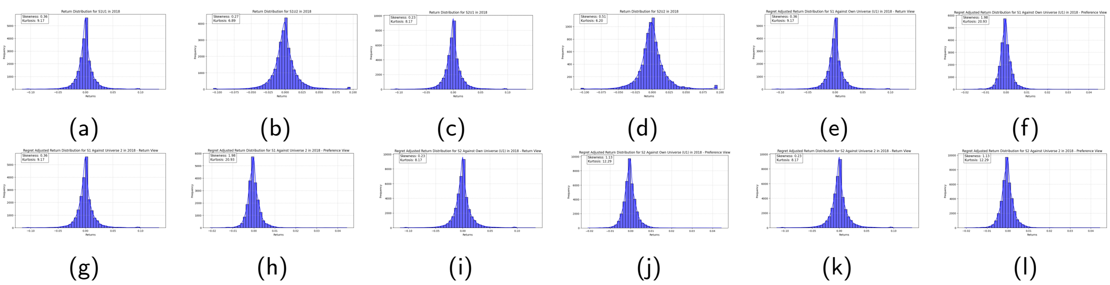
(c) The Relationship in the Dedicated Portfolio for Domestic Investments

Figure B.5: The Relationship between Daily Cross-Sectional Absolute Deviation ($CSAD_t$) and Equally Weighted Small and Medium-Cap Portfolio Returns ($R_{p,t}$) Following the Inclusion of the SSM

Appendix C

An Appendix Chapter Related to Regret Aversion Investigation

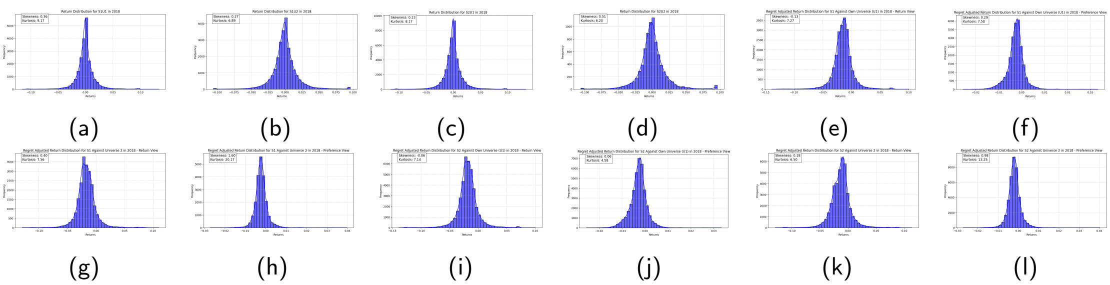
C.0.1 Regret Aversion Sensitivity and Stock-level Return Distributions



(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

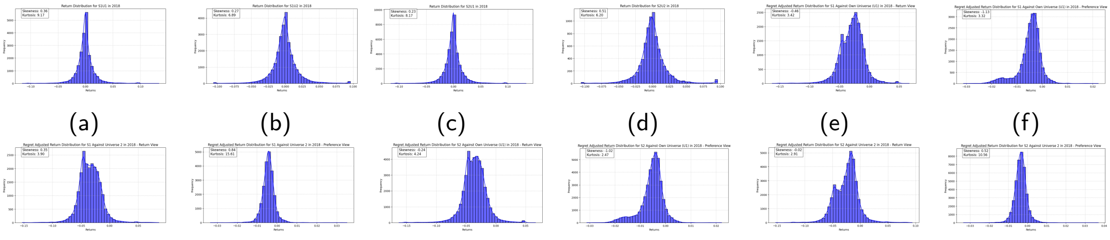
Figure C.1: Original Stock Return Distributions Before Regret Adjustment ($\alpha = 0$) for both Investment Scenarios and Universes in 2018



(a) (b) (c) (d) (e) (f)

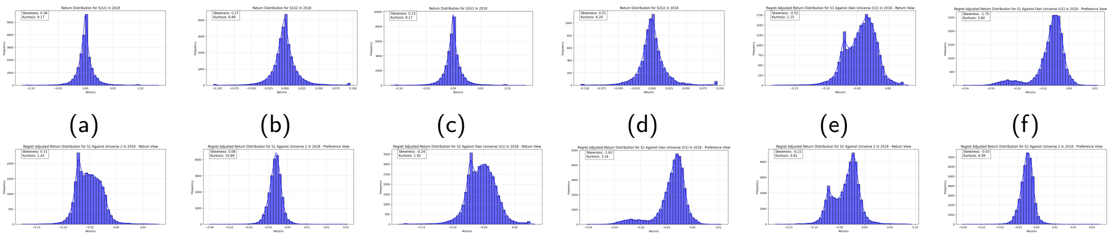
(g) (h) (i) (j) (k) (l)

Figure C.2: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2018 - $\alpha = 0.25$



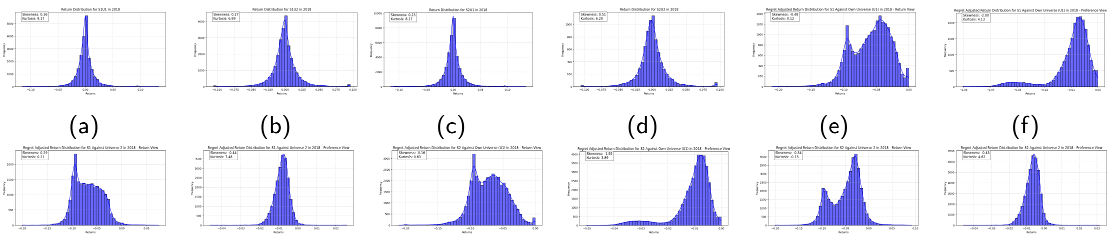
(a) (b) (c) (d) (e) (f)
(g) (h) (i) (j) (k) (l)

Figure C.3: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2018 - $\alpha = 0.50$



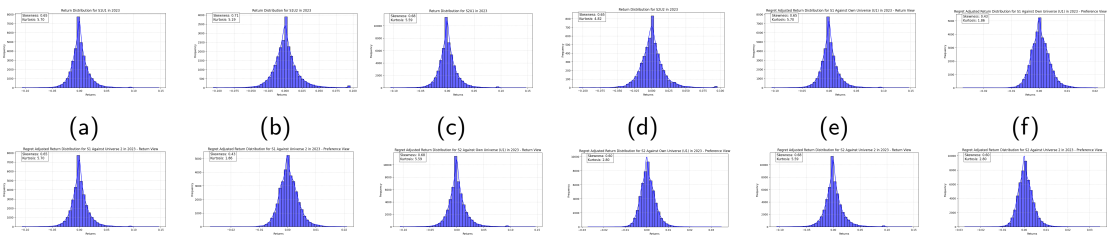
(a) (b) (c) (d) (e) (f)
(g) (h) (i) (j) (k) (l)

Figure C.4: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2018 - $\alpha = 0.75$



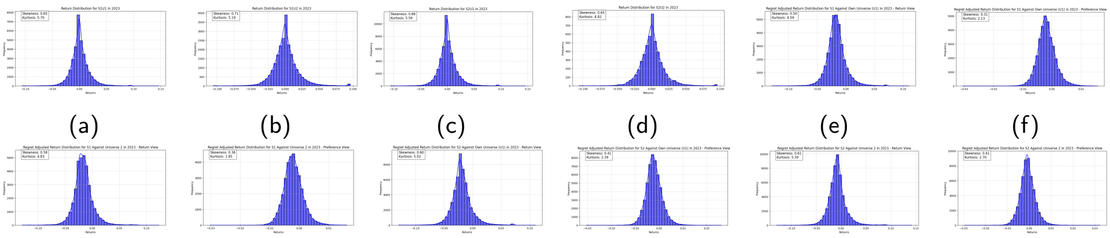
(a) (b) (c) (d) (e) (f)
(g) (h) (i) (j) (k) (l)

Figure C.5: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2018 - $\alpha = 1.00$



(a) (b) (c) (d) (e) (f)
(g) (h) (i) (j) (k) (l)

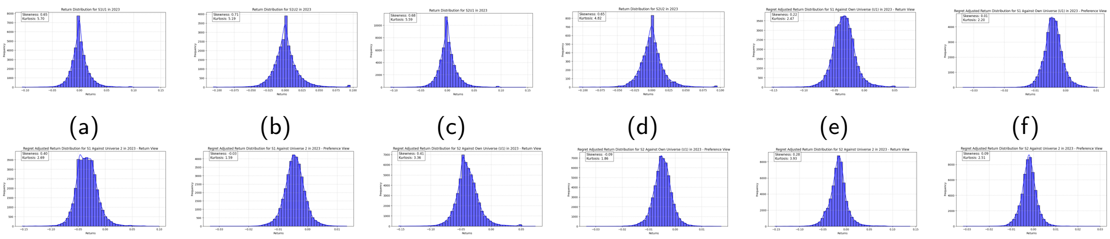
Figure C.6: Original Stock Return Distributions Before Regret Adjustment ($\alpha = 0$) for both Investment Scenarios and Universes in 2023



(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

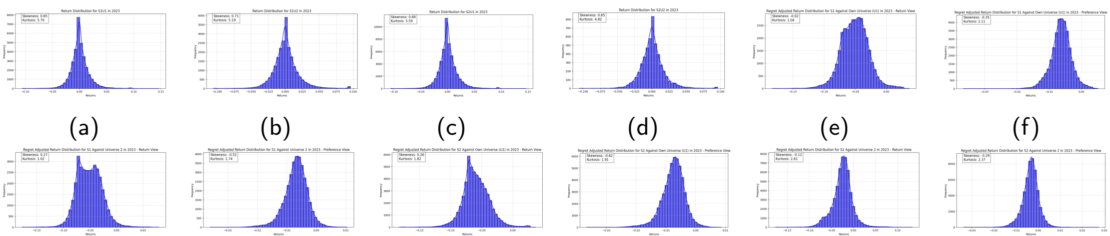
Figure C.7: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2023 - $\alpha = 0.25$



(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

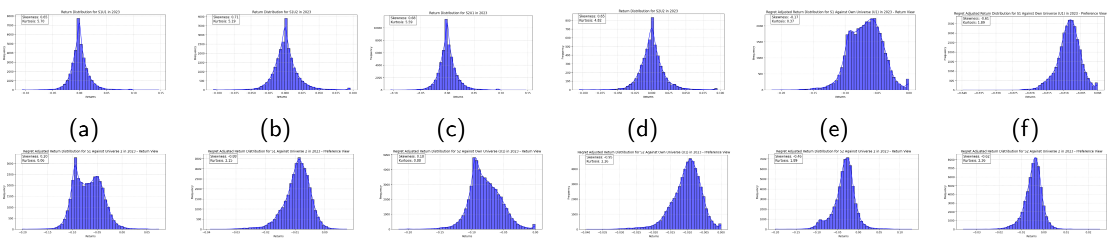
Figure C.8: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2023 - $\alpha = 0.50$



(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

Figure C.9: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2023 - $\alpha = 0.75$

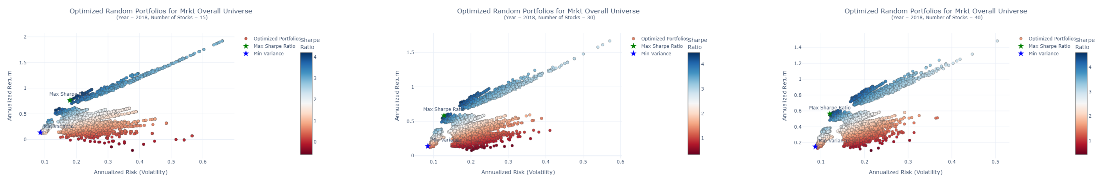


(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

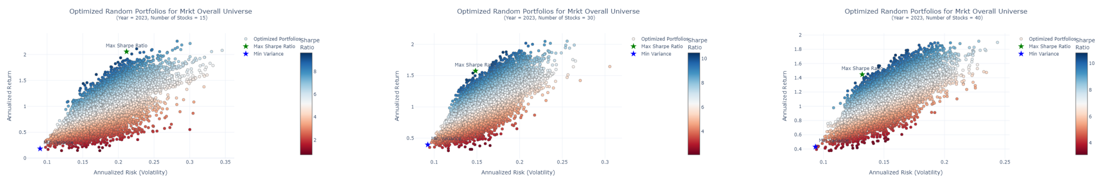
Figure C.10: Regret-adjusted Stock Return Distributions for both Investment Scenarios and Universes in 2023 - $\alpha = 1.00$

C.0.2 Additional Figures Related to the Portfolio Optimization Problem



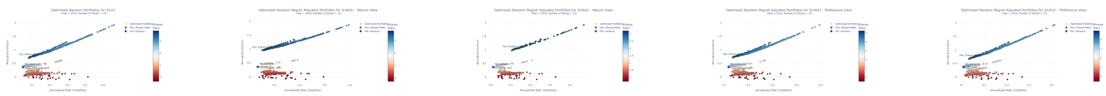
(a) (b) (c)

Figure C.11: Efficient Frontiers for the Overall SSM Using the Classical Markowitz Model with Different Portfolio Size in 2018



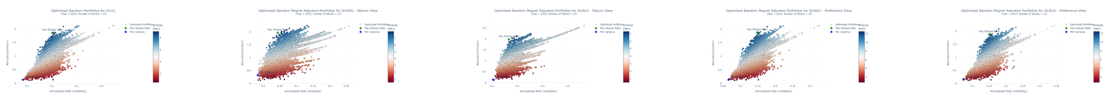
(a) (b) (c)

Figure C.12: Efficient Frontiers for the Overall SSM Using the Classical Markowitz Model with Different Portfolio Size in 2023



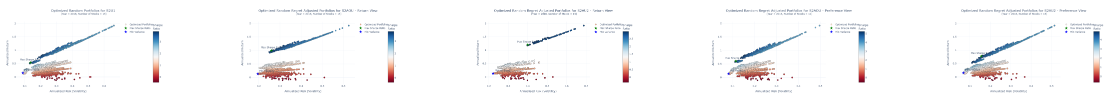
(a) (b) (c) (d) (e)

Figure C.13: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 15 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



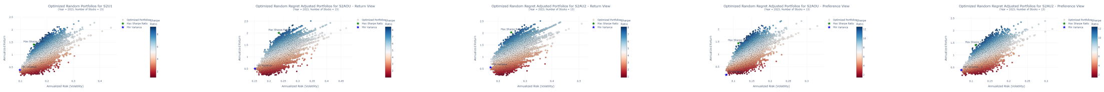
(a) (b) (c) (d) (e)

Figure C.14: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 15 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)



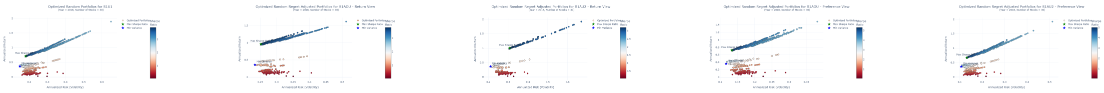
(a) (b) (c) (d) (e)

Figure C.15: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 15 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



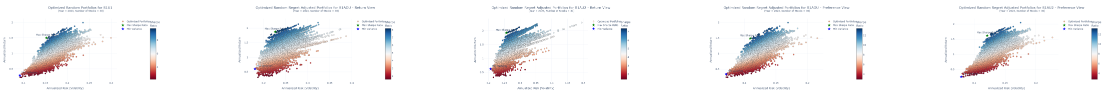
(a) (b) (c) (d) (e)

Figure C.16: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 15 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)



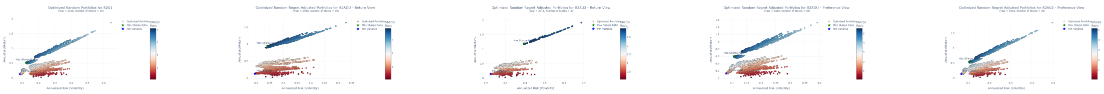
(a) (b) (c) (d) (e)

Figure C.17: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 30 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



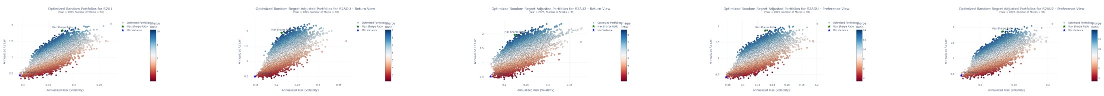
(a) (b) (c) (d) (e)

Figure C.18: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 30 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)



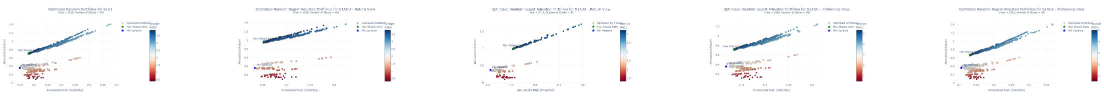
(a) (b) (c) (d) (e)

Figure C.19: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 30 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



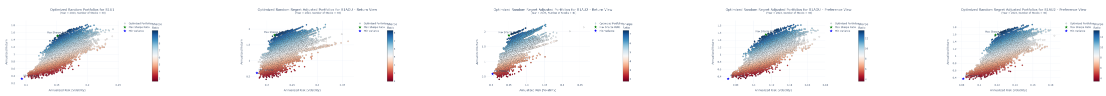
(a) (b) (c) (d) (e)

Figure C.20: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 30 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)



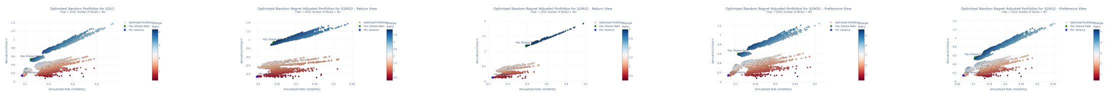
(a) (b) (c) (d) (e)

Figure C.21: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 40 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



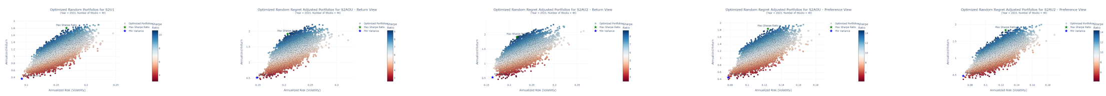
(a) (b) (c) (d) (e)

Figure C.22: Efficient Frontiers for $S1U1$ Using the Classical Markowitz and Regret-augmented Models with 40 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)



(a) (b) (c) (d) (e)

Figure C.23: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 40 Stock Portfolio Size in 2018 - Average Regret Level ($\alpha = 0.5$)



(a) (b) (c) (d) (e)

Figure C.24: Efficient Frontiers for $S2U1$ Using the Classical Markowitz and Regret-augmented Models with 40 Stock Portfolio Size in 2023 - Average Regret Level ($\alpha = 0.5$)

C.0.3 Additional Tables Related to the Portfolio Optimization Problem

Table C.1: Estimated Return Distribution for Strict Shariah Adherent $\mu - \sigma$ portfolios in 2018

$\mu - \sigma$ portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.725	0.710	0.710	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.766	0.582	0.564
			Std. Dev.	0.185	0.180	0.180				Std. Dev.	0.180	0.128	0.120
			Sharpe Ratio	3.872	3.890	3.890				Sharpe Ratio	4.205	4.472	4.602
			Skewness	-0.015	-0.045	-0.045				Skewness	0.064	-0.093	-0.118
			ES at 5%	-0.025	-0.024	-0.024				ES at 5%	-0.023	-0.017	-0.016
			ES at 1%	-0.033	-0.034	-0.034				ES at 1%	-0.030	-0.024	-0.022
	Return View	Avg. Regret Level	Mean Return	0.966	0.963	0.963	Against Universe 2	Return View	Avg. Regret Level	Mean Return	1.011	0.999	0.999
			Std. Dev.	0.252	0.252	0.252				Std. Dev.	0.312	0.308	0.308
			Sharpe Ratio	3.787	3.788	3.788				Sharpe Ratio	3.212	3.214	3.214
			Skewness	0.216	0.218	0.218				Skewness	0.223	0.197	0.197
			ES at 5%	-0.037	-0.037	-0.037				ES at 5%	-0.039	-0.038	-0.038
			ES at 1%	-0.044	-0.044	-0.044				ES at 1%	-0.049	-0.049	-0.049
		Extreme Regret Level	Mean Return	1.569	1.568	1.568			Extreme Regret Level	Mean Return	1.654	1.654	1.654
			Std. Dev.	0.491	0.491	0.491				Std. Dev.	0.607	0.607	0.607
			Sharpe Ratio	3.174	3.174	3.174				Sharpe Ratio	2.708	2.708	2.708
			Skewness	0.314	0.314	0.314				Skewness	0.321	0.321	0.321
			ES at 5%	-0.073	-0.073	-0.073				ES at 5%	-0.078	-0.078	-0.078
			ES at 1%	-0.083	-0.083	-0.083				ES at 1%	-0.088	-0.088	-0.088
	Preference View	Avg. Regret Level	Mean Return	0.732	0.720	0.720		Preference View	Avg. Regret Level	Mean Return	0.685	0.669	0.669
			Std. Dev.	0.136	0.133	0.133				Std. Dev.	0.136	0.132	0.132
			Sharpe Ratio	5.289	5.318	5.318				Sharpe Ratio	4.975	5.010	5.010
			Skewness	-0.004	-0.034	-0.034				Skewness	-0.013	-0.045	-0.045
			ES at 5%	-0.025	-0.025	-0.025				ES at 5%	-0.023	-0.023	-0.023
			ES at 1%	-0.033	-0.034	-0.034				ES at 1%	-0.031	-0.032	-0.032
		Extreme Regret Level	Mean Return	0.803	0.789	0.790			Extreme Regret Level	Mean Return	0.718	0.700	0.700
			Std. Dev.	0.206	0.202	0.202				Std. Dev.	0.188	0.183	0.183
			Sharpe Ratio	3.845	3.854	3.854				Sharpe Ratio	3.757	3.779	3.779
			Skewness	0.016	0.006	0.006				Skewness	-0.012	-0.045	-0.045
			ES at 5%	-0.028	-0.028	-0.028				ES at 5%	-0.025	-0.024	-0.024
			ES at 1%	-0.037	-0.037	-0.037				ES at 1%	-0.033	-0.033	-0.033

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Strict Shariah Adherent mean-variance ($\mu - \sigma$) portfolios in 2018 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.2: Estimated Return Distribution for Moderate Shariah Adherent $\mu-\sigma$ portfolios in 2018

$\mu-\sigma$ portfolios (10K Simulated Portfolios, $\gamma=3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.537	0.523	0.531	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.766	0.582	0.564
			Std. Dev.	0.136	0.124	0.124				Std. Dev.	0.180	0.128	0.120
			Sharpe Ratio	3.882	4.124	4.198				Sharpe Ratio	4.205	4.472	4.602
			Skewness	-0.229	-0.302	-0.280				Skewness	0.064	-0.093	-0.118
			ES at 5%	-0.019	-0.017	-0.017				ES at 5%	-0.023	-0.017	-0.016
			ES at 1%	-0.026	-0.025	-0.025				ES at 1%	-0.030	-0.024	-0.022
	Return View	Avg. Regret Level	Mean Return	0.997	0.942	0.940	Against Universe 2	Return View	Avg. Regret Level	Mean Return	1.202	1.193	1.192
			Std. Dev.	0.260	0.240	0.240				Std. Dev.	0.400	0.394	0.394
			Sharpe Ratio	3.802	3.879	3.880				Sharpe Ratio	2.982	3.001	3.001
			Skewness	0.101	0.095	0.094				Skewness	0.231	0.241	0.241
			ES at 5%	-0.037	-0.034	-0.034				ES at 5%	-0.049	-0.048	-0.048
			ES at 1%	-0.047	-0.043	-0.043				ES at 1%	-0.059	-0.057	-0.057
		Extreme Regret Level	Mean Return	1.397	1.397	1.397			Extreme Regret Level	Mean Return	1.818	1.818	1.818
			Std. Dev.	0.427	0.427	0.427				Std. Dev.	0.717	0.717	0.717
			Sharpe Ratio	3.250	3.250	3.250				Sharpe Ratio	2.520	2.520	2.520
			Skewness	0.275	0.275	0.275				Skewness	0.329	0.329	0.329
			ES at 5%	-0.060	-0.060	-0.060				ES at 5%	-0.090	-0.090	-0.090
			ES at 1%	-0.069	-0.069	-0.069				ES at 1%	-0.098	-0.098	-0.098
	Preference View	Avg. Regret Level	Mean Return	0.610	0.609	0.605		Preference View	Avg. Regret Level	Mean Return	0.775	0.554	0.559
			Std. Dev.	0.114	0.108	0.106				Std. Dev.	0.156	0.105	0.105
			Sharpe Ratio	5.263	5.562	5.634				Sharpe Ratio	4.906	5.163	5.220
			Skewness	-0.140	-0.126	-0.196				Skewness	0.008	-0.237	-0.225
			ES at 5%	-0.022	-0.020	-0.019				ES at 5%	-0.027	-0.018	-0.018
			ES at 1%	-0.029	-0.028	-0.027				ES at 1%	-0.034	-0.025	-0.025
		Extreme Regret Level	Mean Return	0.854	0.797	0.737			Extreme Regret Level	Mean Return	0.799	0.733	0.635
			Std. Dev.	0.219	0.196	0.181				Std. Dev.	0.214	0.188	0.162
			Sharpe Ratio	3.855	4.006	4.012				Sharpe Ratio	3.689	3.845	3.865
			Skewness	0.017	-0.016	-0.053				Skewness	-0.029	-0.059	-0.150
			ES at 5%	-0.030	-0.026	-0.024				ES at 5%	-0.027	-0.024	-0.020
			ES at 1%	-0.038	-0.036	-0.033				ES at 1%	-0.036	-0.033	-0.028

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Moderate Shariah Adherent mean-variance ($\mu-\sigma$) portfolios in 2018 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.3: Estimated Return Distribution for Strict Shariah Adherent $\mu - \sigma$ portfolios in 2023

$\mu - \sigma$ portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	1.846	1.502	1.512	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	2.056	1.575	1.446
			Std. Dev.	0.202	0.152	0.151				Std. Dev.	0.211	0.148	0.132
			Sharpe Ratio	9.029	9.729	9.862				Sharpe Ratio	9.629	10.478	10.798
			Skewness	-0.192	-0.386	-0.456				Skewness	-0.392	-0.181	-0.254
			ES at 5%	-0.025	-0.019	-0.019				ES at 5%	-0.025	-0.017	-0.016
			ES at 1%	-0.038	-0.033	-0.032				ES at 1%	-0.047	-0.031	-0.027
	Return View	Avg. Regret Level	Mean Return	1.967	1.872	1.809	Against Universe 2	Return View	Avg. Regret Level	Mean Return	1.973	1.916	1.877
			Std. Dev.	0.243	0.226	0.215				Std. Dev.	0.267	0.256	0.250
			Sharpe Ratio	7.998	8.187	8.312				Sharpe Ratio	7.321	7.400	7.433
			Skewness	-0.144	-0.104	-0.164				Skewness	-0.172	-0.108	-0.168
			ES at 5%	-0.027	-0.024	-0.023				ES at 5%	-0.027	-0.025	-0.024
			ES at 1%	-0.039	-0.038	-0.036				ES at 1%	-0.039	-0.037	-0.037
		Extreme Regret Level	Mean Return	2.108	2.089	2.084			Extreme Regret Level	Mean Return	2.138	2.138	2.138
			Std. Dev.	0.350	0.346	0.345				Std. Dev.	0.396	0.396	0.396
			Sharpe Ratio	5.970	5.977	5.977				Sharpe Ratio	5.354	5.354	5.354
			Skewness	-0.054	-0.026	-0.032				Skewness	-0.100	-0.100	-0.100
			ES at 5%	-0.032	-0.031	-0.031				ES at 5%	-0.033	-0.033	-0.033
			ES at 1%	-0.045	-0.044	-0.044				ES at 1%	-0.047	-0.047	-0.047
	Preference View	Avg. Regret Level	Mean Return	1.869	1.489	1.558		Preference View	Avg. Regret Level	Mean Return	1.878	1.618	1.590
			Std. Dev.	0.148	0.109	0.114				Std. Dev.	0.150	0.121	0.118
			Sharpe Ratio	12.515	13.437	13.537				Sharpe Ratio	12.413	13.216	13.280
			Skewness	-0.195	-0.383	-0.415				Skewness	-0.181	-0.292	-0.386
			ES at 5%	-0.025	-0.019	-0.020				ES at 5%	-0.025	-0.020	-0.020
			ES at 1%	-0.039	-0.033	-0.033				ES at 1%	-0.038	-0.035	-0.034
		Extreme Regret Level	Mean Return	1.876	1.589	1.561			Extreme Regret Level	Mean Return	1.900	1.661	1.753
			Std. Dev.	0.198	0.156	0.151				Std. Dev.	0.203	0.167	0.175
			Sharpe Ratio	9.385	10.061	10.173				Sharpe Ratio	9.246	9.816	9.878
			Skewness	-0.195	-0.363	-0.421				Skewness	-0.179	-0.273	-0.148
			ES at 5%	-0.025	-0.020	-0.020				ES at 5%	-0.025	-0.021	-0.021
			ES at 1%	-0.039	-0.035	-0.033				ES at 1%	-0.039	-0.035	-0.035

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Strict Shariah Adherent mean-variance ($\mu - \sigma$) portfolios in 2023 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.4: Estimated Return Distribution for Moderate Shariah Adherent $\mu - \sigma$ portfolios in 2023

$\mu - \sigma$ portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A)	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	1.409	1.837	1.804
			Std. Dev.	0.151	0.177	0.167
			Sharpe Ratio	9.198	10.247	10.670
			Skewness	0.071	-0.351	-0.389
			ES at 5%	-0.018	-0.021	-0.021
			ES at 1%	-0.024	-0.036	-0.035
	Return View	Avg. Regret Level	Mean Return	2.010	1.940	1.915
			Std. Dev.	0.235	0.213	0.207
			Sharpe Ratio	8.483	9.033	9.171
			Skewness	-0.383	-0.205	-0.374
			ES at 5%	-0.028	-0.023	-0.023
			ES at 1%	-0.048	-0.035	-0.037
		Extreme Regret Level	Mean Return	2.375	2.169	2.187
			Std. Dev.	0.351	0.312	0.313
			Sharpe Ratio	6.718	6.879	6.927
			Skewness	0.071	-0.139	-0.288
			ES at 5%	-0.034	-0.028	-0.029
			ES at 1%	-0.046	-0.042	-0.047
	Preference View	Avg. Regret Level	Mean Return	1.442	1.863	1.832
			Std. Dev.	0.113	0.131	0.124
			Sharpe Ratio	12.537	14.116	14.592
			Skewness	0.064	-0.340	-0.357
			ES at 5%	-0.018	-0.022	-0.021
			ES at 1%	-0.025	-0.037	-0.035
		Extreme Regret Level	Mean Return	1.890	1.883	1.835
			Std. Dev.	0.200	0.177	0.167
			Sharpe Ratio	9.355	10.505	10.870
			Skewness	-0.338	-0.332	-0.366
			ES at 5%	-0.024	-0.022	-0.021
			ES at 1%	-0.046	-0.037	-0.035

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	2.056	1.575	1.446
			Std. Dev.	0.211	0.148	0.132
			Sharpe Ratio	9.629	10.478	10.798
			Skewness	-0.392	-0.181	-0.254
			ES at 5%	-0.025	-0.017	-0.016
			ES at 1%	-0.047	-0.031	-0.027
Against Universe 2	Return View	Avg. Regret Level	Mean Return	2.036	1.960	1.917
			Std. Dev.	0.249	0.224	0.217
			Sharpe Ratio	8.107	8.648	8.736
			Skewness	-0.443	-0.423	-0.432
			ES at 5%	-0.028	-0.025	-0.024
			ES at 1%	-0.049	-0.041	-0.037
		Extreme Regret Level	Mean Return	2.253	2.261	2.220
			Std. Dev.	0.360	0.355	0.347
			Sharpe Ratio	6.212	6.316	6.346
			Skewness	-0.275	-0.231	-0.312
			ES at 5%	-0.033	-0.031	-0.030
			ES at 1%	-0.054	-0.048	-0.049
	Preference View	Avg. Regret Level	Mean Return	1.408	1.860	1.829
			Std. Dev.	0.112	0.133	0.126
			Sharpe Ratio	12.401	13.890	14.388
			Skewness	0.062	-0.338	-0.364
			ES at 5%	-0.018	-0.022	-0.021
			ES at 1%	-0.025	-0.036	-0.034
		Extreme Regret Level	Mean Return	1.441	1.868	1.822
			Std. Dev.	0.153	0.177	0.166
			Sharpe Ratio	9.314	10.431	10.831
			Skewness	0.085	-0.334	-0.375
			ES at 5%	-0.018	-0.022	-0.021
			ES at 1%	-0.025	-0.037	-0.035

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Moderate Shariah Adherent mean-variance ($\mu - \sigma$) portfolios in 2023 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.5: Estimated Return Distribution for Strict Shariah Adherent Min-Var Portfolios in 2018

Min-Var Portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.362	0.362	0.362	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.135	0.139	0.149
			Std. Dev.	0.148	0.148	0.148				Std. Dev.	0.086	0.085	0.087
			Sharpe Ratio	2.370	2.370	2.370				Sharpe Ratio	1.455	1.515	1.593
			Skewness	0.449	0.448	0.448				Skewness	1.660	1.896	1.368
			ES at 5%	-0.020	-0.020	-0.020				ES at 5%	-0.010	-0.010	-0.011
			ES at 1%	-0.028	-0.028	-0.028				ES at 1%	-0.020	-0.016	-0.019
	Return View	Avg. Regret Level	Mean Return	0.361	0.361	0.361	Against Universe 2	Return View	Avg. Regret Level	Mean Return	0.362	0.362	0.362
			Std. Dev.	0.234	0.234	0.234				Std. Dev.	0.211	0.211	0.211
			Sharpe Ratio	1.500	1.500	1.500				Sharpe Ratio	1.664	1.664	1.664
			Skewness	0.257	0.257	0.259				Skewness	0.108	0.108	0.108
			ES at 5%	-0.020	-0.020	-0.020				ES at 5%	-0.021	-0.021	-0.021
			ES at 1%	-0.029	-0.029	-0.029				ES at 1%	-0.031	-0.031	-0.031
		Extreme Regret Level	Mean Return	0.349	0.349	0.349			Extreme Regret Level	Mean Return	0.365	0.365	0.365
			Std. Dev.	0.383	0.383	0.383				Std. Dev.	0.341	0.341	0.341
			Sharpe Ratio	0.885	0.885	0.885				Sharpe Ratio	1.043	1.043	1.043
			Skewness	0.107	0.107	0.107				Skewness	-0.013	-0.013	-0.013
			ES at 5%	-0.023	-0.023	-0.023				ES at 5%	-0.023	-0.023	-0.023
			ES at 1%	-0.034	-0.034	-0.034				ES at 1%	-0.035	-0.035	-0.035
	Preference View	Avg. Regret Level	Mean Return	0.362	0.362	0.362		Preference View	Avg. Regret Level	Mean Return	0.361	0.361	0.361
			Std. Dev.	0.117	0.117	0.117				Std. Dev.	0.107	0.107	0.107
			Sharpe Ratio	3.003	3.003	3.003				Sharpe Ratio	3.281	3.281	3.281
			Skewness	0.415	0.414	0.415				Skewness	0.423	0.422	0.422
			ES at 5%	-0.020	-0.020	-0.020				ES at 5%	-0.020	-0.020	-0.020
			ES at 1%	-0.028	-0.028	-0.028				ES at 1%	-0.028	-0.028	-0.028
		Extreme Regret Level	Mean Return	0.363	0.363	0.363			Extreme Regret Level	Mean Return	0.361	0.361	0.361
			Std. Dev.	0.169	0.169	0.169				Std. Dev.	0.146	0.146	0.146
			Sharpe Ratio	2.080	2.080	2.080				Sharpe Ratio	2.408	2.408	2.408
			Skewness	0.444	0.444	0.444				Skewness	0.426	0.425	0.425
			ES at 5%	-0.020	-0.020	-0.020				ES at 5%	-0.020	-0.020	-0.020
			ES at 1%	-0.028	-0.028	-0.028				ES at 1%	-0.028	-0.028	-0.028

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Strict Shariah Adherent minimum-variance (Min-Var) portfolios in 2018 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.6: Estimated Return Distribution for Moderate Shariah Adherent Min-Var Portfolios in 2018

Min-Var Portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.150	0.134	0.141
			Std. Dev.	0.088	0.086	0.087
			Sharpe Ratio	1.589	1.446	1.506
			Skewness	1.285	1.458	1.652
			ES at 5%	-0.011	-0.011	-0.011
			ES at 1%	-0.020	-0.021	-0.020
	Return View	Avg. Regret Level	Mean Return	0.129	0.133	0.133
			Std. Dev.	0.195	0.196	0.196
			Sharpe Ratio	0.613	0.625	0.627
			Skewness	1.001	0.611	0.611
			ES at 5%	-0.015	-0.016	-0.016
			ES at 1%	-0.021	-0.024	-0.022
		Extreme Regret Level	Mean Return	0.348	0.348	0.348
			Std. Dev.	0.318	0.318	0.318
			Sharpe Ratio	1.062	1.062	1.062
			Skewness	-0.170	-0.174	-0.174
			ES at 5%	-0.024	-0.024	-0.024
			ES at 1%	-0.037	-0.037	-0.037
	Preference View	Avg. Regret Level	Mean Return	0.133	0.137	0.141
			Std. Dev.	0.081	0.080	0.081
			Sharpe Ratio	1.527	1.580	1.626
			Skewness	1.758	1.345	1.616
			ES at 5%	-0.012	-0.011	-0.011
			ES at 1%	-0.020	-0.021	-0.019
		Extreme Regret Level	Mean Return	0.134	0.134	0.134
			Std. Dev.	0.123	0.123	0.123
			Sharpe Ratio	1.001	1.001	1.001
			Skewness	1.700	1.702	1.702
			ES at 5%	-0.012	-0.012	-0.012
			ES at 1%	-0.020	-0.020	-0.020

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.135	0.139	0.149
			Std. Dev.	0.086	0.085	0.087
			Sharpe Ratio	1.455	1.515	1.593
			Skewness	1.660	1.896	1.368
			ES at 5%	-0.010	-0.010	-0.011
			ES at 1%	-0.020	-0.016	-0.019
Against Universe 2	Return View	Avg. Regret Level	Mean Return	0.133	0.134	0.133
			Std. Dev.	0.222	0.224	0.222
			Sharpe Ratio	0.554	0.554	0.555
			Skewness	0.182	0.201	0.038
			ES at 5%	-0.015	-0.016	-0.017
			ES at 1%	-0.025	-0.025	-0.025
		Extreme Regret Level	Mean Return	0.131	0.130	0.136
			Std. Dev.	0.390	0.396	0.392
			Sharpe Ratio	0.309	0.304	0.321
			Skewness	0.252	1.263	-0.598
			ES at 5%	-0.019	-0.017	-0.026
			ES at 1%	-0.030	-0.023	-0.040
	Preference View	Avg. Regret Level	Mean Return	0.152	0.137	0.140
			Std. Dev.	0.068	0.067	0.068
			Sharpe Ratio	2.080	1.886	1.921
			Skewness	1.030	1.116	1.401
			ES at 5%	-0.012	-0.011	-0.011
			ES at 1%	-0.021	-0.023	-0.021
		Extreme Regret Level	Mean Return	0.136	0.137	0.141
			Std. Dev.	0.099	0.097	0.098
			Sharpe Ratio	1.272	1.310	1.336
			Skewness	1.275	1.011	1.316
			ES at 5%	-0.012	-0.011	-0.011
			ES at 1%	-0.023	-0.023	-0.022

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Moderate Shariah Adherent minimum-variance (Min-Var) portfolios in 2018 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.7: Estimated Return Distribution for Strict Shariah Adherent Min-Var Portfolios in 2023

Min-Var Portfolios (10K Simulated Portfolios, $\gamma = 3$)													
Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.138	0.288	0.326	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.182	0.395	0.430
			Std. Dev.	0.083	0.092	0.093				Std. Dev.	0.090	0.092	0.093
			Sharpe Ratio	1.428	2.926	3.277				Sharpe Ratio	1.792	4.056	4.395
			Skewness	0.275	-0.617	-0.419				Skewness	-0.148	-0.260	-0.173
			ES at 5%	-0.009	-0.013	-0.013				ES at 5%	-0.012	-0.012	-0.013
			ES at 1%	-0.012	-0.019	-0.019				ES at 1%	-0.015	-0.019	-0.019
	Return View	Avg. Regret Level	Mean Return	0.319	0.603	0.616	Against Universe 2	Return View	Avg. Regret Level	Mean Return	0.135	0.617	0.587
			Std. Dev.	0.183	0.180	0.180				Std. Dev.	0.204	0.206	0.204
			Sharpe Ratio	1.636	3.233	3.304				Sharpe Ratio	0.562	2.894	2.780
			Skewness	-0.263	-0.374	-0.394				Skewness	0.236	-0.346	-0.255
			ES at 5%	-0.018	-0.024	-0.023				ES at 5%	-0.016	-0.019	-0.019
			ES at 1%	-0.025	-0.034	-0.031				ES at 1%	-0.021	-0.029	-0.028
		Extreme Regret Level	Mean Return	0.673	0.677	0.674			Extreme Regret Level	Mean Return	0.606	0.559	0.616
			Std. Dev.	0.297	0.299	0.298				Std. Dev.	0.336	0.335	0.333
			Sharpe Ratio	2.198	2.202	2.197				Sharpe Ratio	1.747	1.608	1.792
			Skewness	0.064	-0.066	0.089				Skewness	-0.104	-0.171	-0.041
			ES at 5%	-0.032	-0.032	-0.033				ES at 5%	-0.026	-0.023	-0.023
			ES at 1%	-0.042	-0.044	-0.042				ES at 1%	-0.039	-0.036	-0.030
	Preference View	Avg. Regret Level	Mean Return	0.140	0.342	0.340		Preference View	Avg. Regret Level	Mean Return	0.153	0.254	0.373
			Std. Dev.	0.065	0.071	0.072				Std. Dev.	0.073	0.079	0.082
			Sharpe Ratio	1.826	4.529	4.468				Sharpe Ratio	1.820	2.971	4.303
			Skewness	-0.179	-0.099	-0.376				Skewness	0.400	-0.238	-0.360
			ES at 5%	-0.012	-0.013	-0.014				ES at 5%	-0.011	-0.013	-0.015
			ES at 1%	-0.016	-0.020	-0.020				ES at 1%	-0.014	-0.018	-0.023
		Extreme Regret Level	Mean Return	0.145	0.361	0.370			Extreme Regret Level	Mean Return	0.195	0.389	0.411
			Std. Dev.	0.095	0.103	0.107				Std. Dev.	0.108	0.120	0.125
			Sharpe Ratio	1.320	3.298	3.276				Sharpe Ratio	1.620	3.068	3.120
			Skewness	-0.226	-0.275	-0.363				Skewness	0.139	-0.215	-0.317
			ES at 5%	-0.013	-0.014	-0.015				ES at 5%	-0.012	-0.015	-0.017
			ES at 1%	-0.017	-0.022	-0.022				ES at 1%	-0.014	-0.024	-0.026

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Strict Shariah Adherent minimum-variance (Min-Var) portfolios in 2023 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.8: Estimated Return Distribution for Moderate Shariah Adherent Min-Var Portfolios in 2023

Min-Var Portfolios (10K Simulated Portfolios, $\gamma = 3$)

Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C	Assessed Regret	Regret View	Regret Case	Estimate	Portfolio A	Portfolio B	Portfolio C
Against Universe 1	Classical Markowitz Model	No Regret	Mean Return	0.392	0.443	0.363	The SSM Overall Market	Classical Markowitz Model	No Regret	Mean Return	0.182	0.395	0.430
			Std. Dev.	0.098	0.094	0.092				Std. Dev.	0.090	0.092	0.093
			Sharpe Ratio	3.800	4.495	3.714				Sharpe Ratio	1.792	4.056	4.395
			Skewness	0.424	0.565	0.565				Skewness	-0.148	-0.260	-0.173
			ES at 5%	-0.011	-0.011	-0.011				ES at 5%	-0.012	-0.012	-0.013
			ES at 1%	-0.015	-0.014	-0.016				ES at 1%	-0.015	-0.019	-0.019
	Return View	Avg. Regret Level	Mean Return	0.512	0.501	0.517	Against Universe 2	Return View	Avg. Regret Level	Mean Return	0.563	0.507	0.529
			Std. Dev.	0.152	0.148	0.148				Std. Dev.	0.172	0.168	0.163
			Sharpe Ratio	3.240	3.248	3.350				Sharpe Ratio	3.158	2.894	3.115
			Skewness	0.041	0.050	-0.090				Skewness	-0.068	-0.066	-0.193
			ES at 5%	-0.015	-0.015	-0.015				ES at 5%	-0.017	-0.016	-0.018
			ES at 1%	-0.023	-0.020	-0.020				ES at 1%	-0.027	-0.022	-0.025
		Extreme Regret Level	Mean Return	0.532	0.534	0.496			Extreme Regret Level	Mean Return	0.939	0.923	0.895
			Std. Dev.	0.255	0.254	0.255				Std. Dev.	0.278	0.275	0.274
			Sharpe Ratio	2.011	2.025	1.865				Sharpe Ratio	3.311	3.286	3.188
			Skewness	-0.122	-0.062	0.303				Skewness	-0.061	0.223	0.191
			ES at 5%	-0.019	-0.020	-0.022				ES at 5%	-0.023	-0.024	-0.024
			ES at 1%	-0.028	-0.028	-0.033				ES at 1%	-0.034	-0.033	-0.033
	Preference View	Avg. Regret Level	Mean Return	0.185	0.421	0.450		Preference View	Avg. Regret Level	Mean Return	0.395	0.453	0.472
			Std. Dev.	0.080	0.078	0.078				Std. Dev.	0.074	0.072	0.071
			Sharpe Ratio	2.063	5.158	5.533				Sharpe Ratio	5.093	6.036	6.352
			Skewness	0.154	-0.398	0.850				Skewness	0.459	0.593	0.284
			ES at 5%	-0.012	-0.013	-0.012				ES at 5%	-0.011	-0.011	-0.012
			ES at 1%	-0.016	-0.021	-0.017				ES at 1%	-0.015	-0.014	-0.017
		Extreme Regret Level	Mean Return	0.371	0.427	0.459			Extreme Regret Level	Mean Return	0.410	0.475	0.387
			Std. Dev.	0.113	0.110	0.110				Std. Dev.	0.103	0.102	0.101
			Sharpe Ratio	3.118	3.696	4.008				Sharpe Ratio	3.782	4.452	3.634
			Skewness	0.528	-0.455	0.675				Skewness	0.414	0.583	0.590
			ES at 5%	-0.013	-0.013	-0.012				ES at 5%	-0.012	-0.012	-0.012
			ES at 1%	-0.019	-0.022	-0.018				ES at 1%	-0.016	-0.015	-0.017

Notes. This table presents the estimated return distributions derived from the optimization process for 10,000 simulated Moderate Shariah Adherent minimum-variance (Min-Var) portfolios in 2023 under various regret perspectives and levels. The optimization is conducted under three distinct regret scenarios— Alpha=0 (No Regret), Alpha=0.5 (Average Regret Level), and Alpha=0.9 (Extreme Regret Level)—and applied to both Universe 1 (Shariah-compliant) and Universe 2 (Non-Shariah-compliant). The Monte Carlo simulation was conducted three times, using optimized portfolios comprising 15 in A, 30 in B, and 40 stocks in C. Metrics such as mean return, standard deviation, Sharpe ratio, skewness, and expected shortfall (ES) at 5% and 1% are reported across different regret scenarios. Section C.0.2 in the appendices includes the relevant efficient frontier plots for the estimated portfolios.

Table C.9: Top 10 Optimal Allocations For Strict Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2018 - Portfolio A (N=15)

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)											
Classical Markowitz Investor - No Regret	Stock symbol	4190	1120	4140	4003	1213	4061	3091	4260	4002	2001
	Investment weights	0.366	0.262	0.214	0.131	0.020	0.007	0.000	0.000	0.000	0.000
		(0.241)	(0.144)	(0.134)	(0.047)	(0.007)	(0.003)	(0.000)	(-0.001)	(-0.010)	(0.000)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4140	4190	1120	4003	1213	4061	4240	4090	4002	3091
	Investment weights	0.381	0.189	0.163	0.161	0.074	0.031	0.000	0.000	0.000	0.000
		(0.287)	(0.066)	(0.046)	(0.052)	(0.057)	(0.027)	(0.000)	(0.000)	(-0.007)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4140	4003	1213	4050	4240	2070	2270	4346	2190	4090
	Investment weights	0.734	0.261	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.587)	(0.120)	(-0.012)	(-0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	4190	1120	4140	4003	1213	4061	3007	2001	4260	3091
	Investment weights	0.354	0.252	0.223	0.127	0.029	0.015	0.000	0.000	0.000	0.000
		(0.226)	(0.132)	(0.149)	(0.040)	(0.016)	(0.010)	(0.000)	(0.000)	(-0.001)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	4190	4140	1120	4003	1213	4260	3091	3007	4100	2001
	Investment weights	0.358	0.258	0.216	0.153	0.015	0.000	0.000	0.000	0.000	0.000
		(0.228)	(0.175)	(0.096)	(0.061)	(0.002)	(-0.001)	(0.000)	(0.000)	(-0.009)	(0.000)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4140	4190	4003	4200	1140	1202	4150	4310	2240	1020
	Investment weights	0.389	0.375	0.156	0.075	0.005	0.000	0.000	0.000	0.000	0.000
		(0.282)	(0.246)	(0.056)	(-0.014)	(-0.081)	(-0.003)	(0.000)	(0.000)	(0.000)	(-0.055)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4140	4003	3007	4050	2070	4260	2290	1301	6004	4300
	Investment weights	0.798	0.202	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.638)	(0.077)	(0.000)	(-0.001)	(0.000)	(0.000)	(-0.009)	(0.000)	(-0.001)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	4190	1120	4140	4003	1213	4061	2001	3007	4260	4240
	Investment weights	0.363	0.281	0.196	0.110	0.035	0.014	0.000	0.000	0.000	0.000
		(0.238)	(0.163)	(0.120)	(0.028)	(0.022)	(0.010)	(-0.001)	(0.000)	(-0.001)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	4190	1120	4140	4003	1213	4061	4002	4330	3007	4260
	Investment weights	0.366	0.262	0.212	0.126	0.028	0.006	0.000	0.000	0.000	0.000
		(0.241)	(0.143)	(0.131)	(0.042)	(0.014)	(0.003)	(-0.010)	(0.000)	(0.000)	(-0.001)

Notes. This table displays the top ten optimal asset allocations for strictly Shariah-adherent portfolios, estimated using different investor preference models within the mean-variance optimization framework for the year 2018. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications, and examines multiple portfolio sizes: Portfolio A (N=15 stocks), Portfolio B (N=30 stocks), and Portfolio C (N=40 stocks). This table outlines the optimal allocations for Portfolio A while table C.17 in the appendices details the optimal allocations for Portfolios B and C. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.10: Descriptive Statistics For Top Allocated Stocks of S1U1 in 2018

Utilized Model	Stock Symbol	Obv.	Mean	Std Dev	Minimum	Median	Maximum	Skewness	Kurtosis
Top Allocations Under Classical Markowitz Model	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
	1213	249	0.001	0.028	-0.105	-0.001	0.095	0.275	3.693
	4061	249	0.000	0.022	-0.089	0.000	0.105	0.693	5.352
	4200	249	0.001	0.019	-0.071	0.001	0.095	0.597	4.383
Top Allocations Under Regret-augmented Model - Return View	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
	1213	249	0.001	0.028	-0.105	-0.001	0.095	0.275	3.693
	4061	249	0.000	0.022	-0.089	0.000	0.105	0.693	5.352
	4200	249	0.001	0.019	-0.071	0.001	0.095	0.597	4.383
Top Allocations Under Regret-augmented Model - Preference View	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
	4200	249	0.001	0.019	-0.071	0.001	0.095	0.597	4.383
	1213	249	0.001	0.028	-0.105	-0.001	0.095	0.275	3.693
	4061	249	0.000	0.022	-0.089	0.000	0.105	0.693	5.352
	1140	249	0.001	0.016	-0.098	0.001	0.078	-0.204	8.477

Notes. This table provides a detailed statistical analysis of the stocks that received the highest portfolio weights under various optimization approaches applied to a Strict Shariah-compliant stock universe in 2018. The analysis is structured by portfolio construction methodology including the Classical Markowitz Model, the Regret-augmented Model under the Return View and the Regret-augmented Model under the Preference View. This table presents the statistical characteristics of the stocks that were consistently selected across the different optimal portfolios.

Table C.11: Top 10 Optimal Allocations For Moderate Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2018 - Portfolio A (N=15)

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)											
Classical Markowitz Investor - No Regret	Stock symbol	4291	1120	4140	2210	8210	1140	4344	4335	4040	1210
	Investment weights	0.401	0.219	0.162	0.119	0.051	0.047	0.000	0.000	0.000	0.000
		(0.338)	(0.154)	(0.116)	(0.073)	(0.015)	(-0.005)	(0.000)	(0.000)	(0.000)	(-0.003)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4140	1120	2210	4003	2080	3050	1210	4339	4070	8150
	Investment weights	0.363	0.290	0.192	0.156	0.000	0.000	0.000	0.000	0.000	0.000
		(0.310)	(0.218)	(0.134)	(0.089)	(0.000)	(0.000)	(-0.002)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4140	2210	4003	4150	6020	6002	1212	1214	4336	4180
	Investment weights	0.614	0.231	0.155	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.537)	(0.162)	(0.074)	(0.000)	(0.000)	(-0.001)	(-0.002)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	4291	1120	4140	2210	8210	1140	4344	4260	4335	4040
	Investment weights	0.333	0.230	0.197	0.143	0.061	0.037	0.000	0.000	0.000	0.000
		(0.274)	(0.162)	(0.154)	(0.094)	(0.023)	(-0.015)	(0.000)	(-0.001)	(0.000)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	4190	4140	2210	7010	4050	4005	2360	3060	4342	4338
	Investment weights	0.447	0.288	0.203	0.063	0.000	0.000	0.000	0.000	0.000	0.000
		(0.373)	(0.240)	(0.152)	(0.001)	(-0.001)	(-0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4140	4190	2210	3040	4070	4011	2100	4300	1830	3004
	Investment weights	0.513	0.291	0.196	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.442)	(0.216)	(0.136)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.019)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4140	2210	3001	4320	5110	6090	4333	8110	3080	4291
	Investment weights	0.926	0.074	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.832)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.012)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	4190	4140	2210	1140	8050	1810	2060	2320	3007	4040
	Investment weights	0.470	0.240	0.188	0.102	0.000	0.000	0.000	0.000	0.000	0.000
		(0.400)	(0.195)	(0.142)	(0.050)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	4190	4140	2210	7010	3060	8010	2360	2190	4338	4040
	Investment weights	0.458	0.253	0.200	0.089	0.000	0.000	0.000	0.000	0.000	0.000
		(0.388)	(0.205)	(0.153)	(0.030)	(0.000)	(0.000)	(0.000)	(-0.001)	(0.000)	(0.000)

Notes. This table displays the top ten optimal asset allocations for Moderately Shariah-adherent portfolios, estimated using different investor preference models within the mean-variance optimization framework for the year 2018. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications, and examines multiple portfolio sizes: Portfolio A (N=15 stocks), Portfolio B (N=30 stocks), and Portfolio C (N=40 stocks). This table outlines the optimal allocations for Portfolio A while table C.18 in the appendices details the optimal allocations for Portfolios B and C. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.12: Descriptive Statistics For Top Allocated Stocks of S2U1 in 2018

Utilized Model	Stock Symbol	Obv.	Mean	Std Dev	Minimum	Median	Maximum	Skewness	Kurtosis
Top Allocations Under Classical Markowitz Model	4291	249	0.001	0.007	-0.028	0.000	0.052	3.393	27.53
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	2210	249	0.002	0.025	-0.104	-0.001	0.095	0.784	4.090
	8210	249	0.001	0.020	-0.050	-0.003	0.095	1.590	5.169
	1140	249	0.001	0.016	-0.098	0.001	0.078	-0.204	8.477
	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
Top Allocations Under Regret-augmented Model - Return View	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	2210	249	0.002	0.025	-0.104	-0.001	0.095	0.784	4.090
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	8210	249	0.001	0.020	-0.050	-0.003	0.095	1.590	5.169
	8280	249	0.001	0.025	-0.095	0.000	0.095	-0.133	3.441
Top Allocations Under Regret-augmented Model - Preference View	4291	249	0.001	0.007	-0.028	0.000	0.052	3.393	27.53
	4190	249	0.001	0.013	-0.047	0.000	0.070	0.710	5.709
	4140	249	0.004	0.042	-0.105	-0.001	0.096	0.346	1.658
	2210	249	0.002	0.025	-0.104	-0.001	0.095	0.784	4.090
	4003	249	0.002	0.023	-0.051	-0.001	0.091	0.632	0.649
	1120	249	0.001	0.013	-0.045	0.001	0.064	0.361	2.970
	7010	249	0.001	0.014	-0.064	0.000	0.059	0.169	3.218
	8210	249	0.001	0.020	-0.050	-0.003	0.095	1.590	5.169
	1140	249	0.001	0.016	-0.098	0.001	0.078	-0.204	8.477
	1830	249	0.001	0.013	-0.101	0.000	0.062	-1.357	22.04

Notes. This table provides a detailed statistical analysis of the stocks that received the highest portfolio weights under various optimization approaches applied to a Moderate Shariah-compliant stock universe in 2018. The analysis is structured by portfolio construction methodology including the Classical Markowitz Model, the Regret-augmented Model under the Return View and the Regret-augmented Model under the Preference View. This table presents the statistical characteristics of the stocks that were consistently selected across the different optimal portfolios.

Table C.13: Top 10 Optimal Allocations For Strict Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2023 - Portfolio A (N=15)

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)											
Classical Markowitz Investor - No Regret	Stock symbol	1303	6010	4200	7040	6015	7020	4007	2081	4030	4310
	Investment weights	0.304	0.265	0.235	0.160	0.036	0.000	0.000	0.000	0.000	0.000
		(0.253)	(0.219)	(0.187)	(0.127)	(0.033)	(-0.015)	(-0.011)	(-0.012)	(-0.003)	(-0.009)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	1303	7040	4200	6010	4082	2080	4320	4051	4030	4007
	Investment weights	0.292	0.241	0.238	0.229	0.000	0.000	0.000	0.000	0.000	0.000
		(0.227)	(0.194)	(0.174)	(0.168)	(0.000)	(-0.002)	(-0.004)	(0.000)	(0.000)	(-0.010)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	7040	1303	6010	4200	2081	2080	4310	1301	6015	4007
	Investment weights	0.358	0.307	0.205	0.130	0.000	0.000	0.000	0.000	0.000	0.000
		(0.287)	(0.224)	(0.127)	(0.051)	(-0.004)	(-0.001)	(-0.001)	(0.000)	(0.000)	(-0.008)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	1303	6010	4200	7040	6015	4051	4082	1301	2080	4007
	Investment weights	0.308	0.272	0.227	0.166	0.028	0.000	0.000	0.000	0.000	0.000
		(0.255)	(0.224)	(0.179)	(0.133)	(0.025)	(0.000)	(0.000)	(0.000)	(-0.005)	(-0.012)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	1303	6010	4200	7040	6015	4051	4082	1301	2080	4320
	Investment weights	0.307	0.273	0.231	0.167	0.023	0.000	0.000	0.000	0.000	0.000
		(0.254)	(0.225)	(0.182)	(0.133)	(0.021)	(0.000)	(0.000)	(0.000)	(-0.005)	(-0.015)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	1303	6010	7040	4200	4082	4051	4320	1301	2080	7020
	Investment weights	0.307	0.255	0.228	0.210	0.000	0.000	0.000	0.000	0.000	0.000
		(0.236)	(0.188)	(0.176)	(0.142)	(0.000)	(0.000)	(-0.003)	(0.000)	(-0.002)	(-0.007)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	7040	1303	6010	4200	2081	4051	6015	2080	4030	1301
	Investment weights	0.347	0.340	0.254	0.059	0.000	0.000	0.000	0.000	0.000	0.000
		(0.271)	(0.251)	(0.170)	(-0.021)	(-0.003)	(0.000)	(0.000)	(-0.001)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	7040	6010	4082	4051	4007	1301	4320	4030	2080	2081
	Investment weights	0.164	0.269	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.129)	(0.219)	(0.000)	(0.000)	(-0.012)	(0.000)	(-0.013)	(-0.003)	(-0.006)	(-0.011)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	1303	6010	4200	7040	6015	4007	7020	4320	2081	4051
	Investment weights	0.317	0.272	0.237	0.166	0.009	0.000	0.000	0.000	0.000	0.000
		(0.261)	(0.221)	(0.184)	(0.129)	(0.007)	(-0.012)	(-0.016)	(-0.013)	(-0.011)	(0.000)

Notes. This table displays the top ten optimal asset allocations for strictly Shariah-adherent portfolios, estimated using different investor preference models within the mean-variance optimization framework for the year 2023. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications, and examines multiple portfolio sizes: Portfolio A (N=15 stocks), Portfolio B (N=30 stocks), and Portfolio C (N=40 stocks). This table outlines the optimal allocations for Portfolio A while table C.19 in the appendices details the optimal allocations for Portfolios B and C. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.14: Descriptive Statistics For Top Allocated Stocks of S1U1 in 2023

Utilized Model	Stock Symbol	Obv.	Mean	Std Dev	Minimum	Median	Maximum	Skewness	Kurtosis
	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
	4200	249	0.004	0.020	-0.049	0.001	0.095	0.666	2.128
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	7203	249	0.004	0.023	-0.049	0.002	0.095	0.952	2.270
	4290	249	0.003	0.019	-0.063	0.000	0.072	0.462	1.144
	4334	249	0.000	0.007	-0.036	0.000	0.031	-0.287	3.805
Top Allocations Under Classical Markowitz Model	4050	249	0.003	0.022	-0.074	0.003	0.095	0.561	2.120
	2320	249	0.003	0.018	-0.043	0.002	0.095	0.709	2.755
	1320	249	0.003	0.021	-0.105	0.000	0.095	0.407	5.121
	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	4200	249	0.004	0.020	-0.049	0.001	0.095	0.666	2.128
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
Top Allocations Under Regret-augmented Model - Return View	7203	249	0.004	0.023	-0.049	0.002	0.095	0.952	2.270
	2370	249	0.003	0.022	-0.054	0.001	0.095	0.822	2.380
	1831	249	0.003	0.021	-0.105	0.002	0.092	-0.100	5.037
	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
	4200	249	0.004	0.020	-0.049	0.001	0.095	0.666	2.128
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	7203	249	0.004	0.023	-0.049	0.002	0.095	0.952	2.270
	4334	249	0.000	0.007	-0.036	0.000	0.031	-0.287	3.805
	4290	249	0.003	0.019	-0.063	0.000	0.072	0.462	1.144
	4050	249	0.003	0.022	-0.074	0.003	0.095	0.561	2.120
Top Allocations Under Regret-augmented Model - Preference View	2320	249	0.003	0.018	-0.043	0.002	0.095	0.709	2.755
	1320	249	0.003	0.021	-0.105	0.000	0.095	0.407	5.121
	2370	249	0.003	0.022	-0.054	0.001	0.095	0.822	2.380

Notes. This table provides a detailed statistical analysis of the stocks that received the highest portfolio weights under various optimization approaches applied to a Strict Shariah-compliant stock universe in 2023. The analysis is structured by portfolio construction methodology including the Classical Markowitz Model, the Regret-augmented Model under the Return View and the Regret-augmented Model under the Preference View. This table presents the statistical characteristics of the stocks that were consistently selected across the different optimal portfolios.

Table C.15: Top 10 Optimal Allocations For Moderate Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2023 - Portfolio A (N=15)

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)											
Classical Markowitz Investor - No Regret	Stock symbol	1303	2382	4009	4050	1320	6004	4012	4014	2170	4330
	Investment weights	0.249	0.238	0.196	0.140	0.112	0.057	0.008	0.000	0.000	0.000
		(0.221)	(0.217)	(0.166)	(0.118)	(0.094)	(0.045)	(0.006)	(0.000)	(0.000)	(0.000)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4009	6010	7040	8050	4050	3050	2281	4330	2290	3001
	Investment weights	0.295	0.208	0.199	0.159	0.139	0.000	0.000	0.000	0.000	0.000
		(0.257)	(0.175)	(0.173)	(0.138)	(0.113)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4009	7040	1303	4337	1322	4190	2170	6050	6013	2120
	Investment weights	0.441	0.280	0.279	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.387)	(0.240)	(0.231)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	1303	2382	4009	4050	1320	6004	2170	1020	7200	4220
	Investment weights	0.260	0.218	0.198	0.144	0.119	0.060	0.000	0.000	0.000	0.000
		(0.230)	(0.198)	(0.169)	(0.122)	(0.100)	(0.047)	(0.000)	(0.000)	(-0.006)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	1303	4009	6010	2320	3091	2001	2170	4082	4161	1120
	Investment weights	0.310	0.277	0.226	0.172	0.015	0.000	0.000	0.000	0.000	0.000
		(0.279)	(0.245)	(0.197)	(0.148)	(0.015)	(0.000)	(0.000)	(0.000)	(-0.001)	(0.000)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)											
Avg. Return-regret Investor -(Alpha=0.5)	Stock symbol	4009	6010	7040	8050	4050	2281	2290	3050	3001	7200
	Investment weights	0.289	0.235	0.213	0.153	0.111	0.000	0.000	0.000	0.000	0.000
		(0.248)	(0.199)	(0.185)	(0.131)	(0.084)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.003)
Extreme Return-regret Investor - (Alpha=0.9)	Stock symbol	4009	7040	6010	8050	4050	4191	4020	2281	3050	2290
	Investment weights	0.386	0.303	0.205	0.105	0.000	0.000	0.000	0.000	0.000	0.000
		(0.330)	(0.260)	(0.159)	(0.074)	(-0.031)	(0.000)	(-0.001)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Stock symbol	1303	2382	4009	4050	1320	6004	4012	3092	7202	2170
	Investment weights	0.260	0.245	0.186	0.132	0.128	0.048	0.000	0.000	0.000	0.000
		(0.230)	(0.223)	(0.156)	(0.111)	(0.108)	(0.035)	(-0.001)	(0.000)	(-0.006)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Stock symbol	1303	2382	4009	4050	1320	6004	7202	1020	3092	4012
	Investment weights	0.264	0.229	0.198	0.136	0.126	0.047	0.000	0.000	0.000	0.000
		(0.234)	(0.207)	(0.167)	(0.114)	(0.106)	(0.035)	(-0.006)	(0.000)	(0.000)	(-0.001)

Notes. This table shows the top ten optimal asset allocations for Moderately Shariah-adherent portfolios in 2023, estimated using various investor preference models within the mean-variance optimization framework. The analysis includes three panels based on different modeling approaches and investor preferences, covering Portfolio A (15 stocks), Portfolio B (30 stocks), and Portfolio C (40 stocks). This table focuses on Portfolio A; allocations for Portfolios B and C appear in Table C.20 in the appendices. Each panel lists stock symbols and optimal weights, with parentheses showing deviations from the means.

Table C.16: Descriptive Statistics For Top Allocated Stocks of S2U1 in 2023

Utilized Model	Stock Symbol	Obv.	Mean	Std Dev	Minimum	Median	Maximum	Skewness	Kurtosis
Top Allocations Under Classical Markowitz Model	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	2382	249	0.001	0.011	-0.028	0.000	0.082	3.880	24.675
	4009	249	0.005	0.026	-0.105	0.002	0.095	0.653	2.993
	4050	249	0.003	0.022	-0.074	0.003	0.095	0.561	2.120
	1320	249	0.003	0.021	-0.105	0.000	0.095	0.407	5.121
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
	7203	249	0.004	0.023	-0.049	0.002	0.095	0.952	2.270
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	1830	249	0.004	0.022	-0.064	0.002	0.072	-0.063	0.753
	2320	249	0.003	0.018	-0.043	0.002	0.095	0.709	2.755
	4142	249	0.004	0.022	-0.074	0.002	0.095	0.479	2.001
Top Allocations Under Regret-augmented Model - Return View	4009	249	0.005	0.026	-0.105	0.002	0.095	0.653	2.993
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	8050	249	0.003	0.028	-0.070	0.001	0.096	0.938	1.991
	4050	249	0.003	0.022	-0.074	0.003	0.095	0.561	2.120
	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	4142	249	0.004	0.022	-0.074	0.002	0.095	0.479	2.001
	1830	249	0.004	0.022	-0.064	0.002	0.072	-0.063	0.753
	8311	249	0.002	0.024	-0.104	0.001	0.095	0.538	3.929
Top Allocations Under Regret-augmented Model - Preference View	1303	249	0.004	0.023	-0.084	0.000	0.093	0.696	3.002
	2382	249	0.001	0.011	-0.028	0.000	0.082	3.880	24.675
	4009	249	0.005	0.026	-0.105	0.002	0.095	0.653	2.993
	4050	249	0.003	0.022	-0.074	0.003	0.095	0.561	2.120
	1320	249	0.003	0.021	-0.105	0.000	0.095	0.407	5.121
	6010	249	0.004	0.024	-0.105	0.002	0.094	-0.013	3.068
	7203	249	0.004	0.023	-0.049	0.002	0.095	0.952	2.270
	7040	249	0.005	0.035	-0.105	-0.001	0.095	0.448	1.607
	1830	249	0.004	0.022	-0.064	0.002	0.072	-0.063	0.753
	4142	249	0.004	0.022	-0.074	0.002	0.095	0.479	2.001
	2320	249	0.003	0.018	-0.043	0.002	0.095	0.709	2.755

Notes. This table provides a detailed statistical analysis of the stocks that received the highest portfolio weights under various optimization approaches applied to a Moderate Shariah-compliant stock universe in 2023. The analysis is structured by portfolio construction methodology including the Classical Markowitz Model, the Regret-augmented Model under the Return View and the Regret-augmented Model under the Preference View. This table presents the statistical characteristics of the stocks that were consistently selected across the different optimal portfolios.

Table C.17: Top 10 Optimal Allocations For Strict Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2018 - Portfolios B & C

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)												
Classical Markowitz Investor - No Regret	Portfolio B (N=30)	Stock symbol	4190	1120	4140	4003	4200	1213	4300	4008	4331	3005
		Investment weights	0.351	0.250	0.204	0.121	0.063	0.011	0.000	0.000	0.000	0.000
			(0.160)	(0.075)	(0.090)	(0.011)	(-0.017)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4190	1120	4140	4003	4200	1213	4004	4008	2040	3005
		Investment weights	0.351	0.250	0.204	0.121	0.063	0.011	0.000	0.000	0.000	0.000
			(0.127)	(0.049)	(0.072)	(0.003)	(-0.018)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4140	4190	1120	4003	1213	4061	4200	4004	2340	3001
		Investment weights	0.378	0.186	0.159	0.158	0.072	0.026	0.021	0.000	0.000	0.000
			(0.218)	(0.017)	(-0.001)	(0.002)	(0.057)	(0.016)	(-0.076)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	4190	1120	4003	1213	4061	4200	1320	4130	4002
		Investment weights	0.378	0.186	0.159	0.158	0.072	0.026	0.021	0.000	0.000	0.000
			(0.177)	(0.006)	(-0.014)	(-0.014)	(0.05)	(0.012)	(-0.071)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4140	4003	1213	1150	4040	4333	4260	4180	4345	2170
		Investment weights	0.734	0.261	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.455)	(0.022)	(-0.004)	(-0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	4003	1213	4061	3005	2240	6001	4338	2070	4002
		Investment weights	0.734	0.261	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.371)	(-0.023)	(-0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4190	1120	4140	4003	4200	1213	4300	4008	3005	4331
		Investment weights	0.339	0.240	0.213	0.117	0.072	0.020	0.000	0.000	0.000	0.000
			(0.146)	(0.064)	(0.103)	(0.003)	(-0.014)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4190	1120	4140	4003	4200	1213	4004	4300	3005	2240
		Investment weights	0.339	0.240	0.213	0.117	0.072	0.020	0.000	0.000	0.000	0.000
			(0.115)	(0.041)	(0.082)	(-0.006)	(-0.015)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4190	4140	1120	4003	4200	1213	4010	4150	6090	6020
		Investment weights	0.342	0.250	0.206	0.144	0.052	0.006	0.000	0.000	0.000	0.000
			(0.146)	(0.125)	(0.033)	(0.019)	(-0.033)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4190	4140	1120	4003	4200	1213	6060	3001	1150	2190
		Investment weights	0.342	0.250	0.206	0.144	0.052	0.006	0.000	0.000	0.000	0.000
			(0.115)	(0.100)	(0.012)	(0.007)	(-0.031)	(-0.001)	(0.000)	(0.000)	(-0.015)	(0.000)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4140	4190	4003	4200	1120	4310	4008	6001	4342	1320
		Investment weights	0.383	0.344	0.149	0.072	0.053	0.000	0.000	0.000	0.000	0.000
			(0.211)	(0.153)	(0.013)	(-0.032)	(-0.086)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.001)
	Portfolio C (N=40)	Stock symbol	4140	4190	4003	4200	1120	3090	4080	3005	3001	4333
		Investment weights	0.383	0.344	0.149	0.072	0.053	0.000	0.000	0.000	0.000	0.000
			(0.172)	(0.124)	(0.002)	(-0.033)	(-0.086)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4140	4003	4170	4011	4346	4240	2180	2120	1120	6001
		Investment weights	0.798	0.202	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.490)	(0.005)	(-0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.087)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	4003	3090	4240	4150	4004	4340	2270	4110	3080
		Investment weights	0.798	0.202	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.398)	(-0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4190	1120	4140	4003	4200	1213	1140	4100	1020	2020
		Investment weights	0.342	0.262	0.184	0.097	0.078	0.024	0.013	0.000	0.000	0.000
			(0.153)	(0.086)	(0.079)	(-0.006)	(-0.007)	(0.016)	(-0.083)	(-0.001)	(-0.033)	(-0.016)
	Portfolio C (N=40)	Stock symbol	4190	1120	4140	4003	4200	1213	1140	4300	3005	2040
		Investment weights	0.342	0.262	0.184	0.097	0.078	0.024	0.013	0.000	0.000	0.000
			(0.121)	(0.058)	(0.063)	(-0.012)	(-0.008)	(0.014)	(-0.073)	(0.000)	(0.000)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4190	1120	4140	4003	4200	1213	1140	1150	1020	4002
		Investment weights	0.347	0.248	0.200	0.114	0.073	0.017	0.001	0.000	0.000	0.000
			(0.157)	(0.073)	(0.087)	(0.005)	(-0.011)	(0.009)	(-0.093)	(-0.041)	(-0.031)	(-0.002)
	Portfolio C (N=40)	Stock symbol	4190	1120	4140	4003	4200	1213	1140	7010	1020	6060
		Investment weights	0.347	0.248	0.200	0.114	0.073	0.017	0.001	0.000	0.000	0.000
			(0.124)	(0.048)	(0.069)	(-0.002)	(-0.012)	(0.009)	(-0.081)	(-0.106)	(-0.014)	(-0.001)

Notes. This table displays the top ten optimal asset allocations for strictly Shariah-adherent portfolios B and C, estimated using different investor preference models within the mean-variance optimization framework for the year 2018. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.18: Top 10 Optimal Allocations For Moderate Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2018 - Portfolios B & C

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)												
Classical Markowitz Investor - No Regret	Portfolio B (N=30)	Stock symbol	4291	4190	4140	1120	2210	8210	4300	2040	2200	2060
		Investment weights	0.361	0.233	0.144	0.139	0.103	0.020	0.000	0.000	0.000	0.000
			(0.251)	(0.124)	(0.077)	(0.040)	(0.047)	(-0.021)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4291	4190	4140	1120	2210	4003	8110	8070	4300	4009
		Investment weights	0.354	0.222	0.138	0.126	0.092	0.067	0.000	0.000	0.000	0.000
			(0.222)	(0.095)	(0.063)	(0.012)	(0.032)	(-0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4140	4190	2210	1120	4003	8210	2030	2020	2070	4030
		Investment weights	0.335	0.216	0.155	0.141	0.122	0.032	0.000	0.000	0.000	0.000
			(0.244)	(0.098)	(0.077)	(0.030)	(0.029)	(-0.016)	(-0.055)	(-0.016)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	4190	2210	1120	4003	8210	8280	2050	4009	1810
		Investment weights	0.334	0.215	0.152	0.136	0.119	0.030	0.014	0.000	0.000	0.000
			(0.224)	(0.078)	(0.065)	(0.008)	(0.016)	(-0.018)	(-0.014)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4140	2210	4003	4009	8020	4150	6040	4250	1304	4031
		Investment weights	0.614	0.231	0.155	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.470)	(0.124)	(0.029)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	2210	4003	4220	3007	2240	8080	3050	8020	4160
		Investment weights	0.614	0.231	0.155	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.433)	(0.105)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4291	4190	4140	2210	4003	1140	1150	4100	2030	2002
		Investment weights	0.325	0.287	0.176	0.128	0.085	0.000	0.000	0.000	0.000	0.000
			(0.231)	(0.172)	(0.111)	(0.066)	(0.014)	(-0.061)	(-0.037)	(-0.001)	(-0.035)	(-0.029)
	Portfolio C (N=40)	Stock symbol	4291	4190	4140	1120	2210	4003	4220	2240	3005	4320
		Investment weights	0.280	0.237	0.170	0.123	0.114	0.077	0.000	0.000	0.000	0.000
			(0.169)	(0.102)	(0.095)	(0.003)	(0.047)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4190	4140	1120	2210	4003	8210	2050	3050	2030	2020
		Investment weights	0.297	0.244	0.159	0.139	0.117	0.045	0.000	0.000	0.000	0.000
			(0.177)	(0.169)	(0.051)	(0.072)	(0.038)	(0.001)	(0.000)	(0.000)	(-0.036)	(-0.015)
	Portfolio C (N=40)	Stock symbol	4190	4140	2210	1120	4291	4003	7010	1140	4100	1150
		Investment weights	0.277	0.226	0.134	0.131	0.129	0.104	0.000	0.000	0.000	0.000
			(0.135)	(0.138)	(0.060)	(0.007)	(0.045)	(0.018)	(-0.09)	(-0.055)	(0.000)	(-0.023)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4140	4190	2210	4003	2050	4333	1214	4009	3050	4031
		Investment weights	0.493	0.224	0.163	0.120	0.000	0.000	0.000	0.000	0.000	0.000
			(0.365)	(0.102)	(0.080)	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	4190	2210	4003	4250	1304	8280	1140	2040	1830
		Investment weights	0.493	0.224	0.163	0.120	0.000	0.000	0.000	0.000	0.000	0.000
			(0.336)	(0.080)	(0.072)	(0.007)	(0.000)	(0.000)	(-0.023)	(-0.063)	(0.000)	(-0.003)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4140	2210	4240	1304	4009	2270	2170	6020	8010	2180
		Investment weights	0.926	0.074	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.733)	(-0.037)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4140	2210	1330	1810	1304	5110	2290	4336	3091	4002
		Investment weights	0.926	0.074	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.675)	(-0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4291	4190	1120	4140	2210	8210	4300	2200	5110	2040
		Investment weights	0.277	0.258	0.163	0.150	0.118	0.034	0.000	0.000	0.000	0.000
			(0.175)	(0.148)	(0.062)	(0.086)	(0.062)	(-0.007)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4291	4190	1120	4140	2210	4003	1830	4061	4100	6060
		Investment weights	0.277	0.250	0.151	0.143	0.110	0.065	0.004	0.000	0.000	0.000
			(0.155)	(0.121)	(0.034)	(0.071)	(0.049)	(-0.003)	(-0.017)	(-0.002)	(0.000)	(-0.001)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4190	4140	1120	2210	4003	8210	2030	4345	2020	4340
		Investment weights	0.310	0.205	0.194	0.134	0.103	0.053	0.000	0.000	0.000	0.000
			(0.198)	(0.136)	(0.092)	(0.075)	(0.035)	(0.011)	(-0.036)	(0.000)	(-0.016)	(0.000)
	Portfolio C (N=40)	Stock symbol	4190	4291	4140	1120	2210	4003	1140	2030	1150	4100
		Investment weights	0.274	0.192	0.174	0.154	0.123	0.084	0.000	0.000	0.000	0.000
			(0.142)	(0.082)	(0.095)	(0.036)	(0.059)	(0.011)	(-0.061)	(-0.032)	(-0.029)	(0.000)

Notes. This table displays the top ten optimal asset allocations for moderately Shariah-adherent portfolios B and C, estimated using different investor preference models within the mean-variance optimization framework for the year 2018. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.19: Top 10 Optimal Allocations For Strict Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2023 - Portfolios B & C

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)												
Classical Markowitz Investor - No Regret	Portfolio B (N=30)	Stock symbol	6010	1303	4200	7203	7040	4290	4334	4015	1831	2270
		Investment weights	0.192	0.172	0.131	0.125	0.107	0.071	0.064	0.052	0.042	0.041
			(0.128)	(0.098)	(0.072)	(0.070)	(0.063)	(0.034)	(0.033)	(0.034)	(0.008)	(0.015)
	Portfolio C (N=40)	Stock symbol	6010	1303	7203	4050	7040	2320	1320	4290	2270	4260
		Investment weights	0.186	0.182	0.119	0.114	0.095	0.074	0.064	0.061	0.047	0.021
			(0.111)	(0.097)	(0.056)	(0.060)	(0.046)	(0.020)	(0.023)	(0.022)	(0.019)	(-0.003)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	1303	7040	6010	4200	7203	1320	4190	4331	4081	6015
		Investment weights	0.227	0.214	0.202	0.187	0.126	0.045	0.000	0.000	0.000	0.000
			(0.126)	(0.142)	(0.116)	(0.102)	(0.055)	(-0.007)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	7040	1303	6010	4200	7203	2370	4050	2160	4031	1302
		Investment weights	0.198	0.190	0.179	0.136	0.124	0.104	0.054	0.015	0.000	0.000
			(0.114)	(0.074)	(0.081)	(0.041)	(0.045)	(0.026)	(-0.015)	(-0.018)	(-0.013)	(-0.013)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	7040	1303	6010	4200	7203	4335	4082	4090	2210	6002
		Investment weights	0.353	0.287	0.200	0.116	0.044	0.000	0.000	0.000	0.000	0.000
			(0.234)	(0.149)	(0.085)	(0.011)	(-0.042)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	7040	1303	6010	4200	7203	2370	4330	4323	3030	4170
		Investment weights	0.351	0.284	0.198	0.114	0.045	0.009	0.000	0.000	0.000	0.000
			(0.209)	(0.120)	(0.068)	(-0.001)	(-0.046)	(-0.085)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	6010	1303	4200	7203	7040	4334	4290	4015	1831	2270
		Investment weights	0.190	0.173	0.124	0.123	0.111	0.083	0.062	0.057	0.042	0.034
			(0.124)	(0.097)	(0.065)	(0.067)	(0.066)	(0.051)	(0.028)	(0.037)	(0.007)	(0.009)
	Portfolio C (N=40)	Stock symbol	6010	1303	7203	4050	7040	2320	1320	4290	2270	4260
		Investment weights	0.192	0.191	0.124	0.111	0.105	0.073	0.065	0.056	0.039	0.017
			(0.116)	(0.103)	(0.061)	(0.058)	(0.055)	(0.020)	(0.023)	(0.020)	(0.013)	(-0.006)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	6010	1303	4200	7203	7040	4290	4015	1831	2270	4334
		Investment weights	0.205	0.185	0.137	0.132	0.119	0.068	0.058	0.040	0.037	0.018
			(0.137)	(0.106)	(0.076)	(0.075)	(0.072)	(0.031)	(0.038)	(0.005)	(0.011)	(-0.003)
	Portfolio C (N=40)	Stock symbol	6010	1303	7203	4050	7040	2320	1320	4290	2270	4260
		Investment weights	0.194	0.188	0.125	0.114	0.104	0.078	0.063	0.057	0.040	0.016
			(0.115)	(0.097)	(0.059)	(0.058)	(0.051)	(0.021)	(0.02)	(0.019)	(0.012)	(-0.008)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	1303	6010	7040	4200	7203	1831	4290	2270	4015	4334
		Investment weights	0.257	0.238	0.214	0.178	0.098	0.015	0.000	0.000	0.000	0.000
			(0.144)	(0.140)	(0.134)	(0.086)	(0.025)	(-0.037)	(-0.043)	(-0.012)	(-0.006)	(0.000)
	Portfolio C (N=40)	Stock symbol	1303	6010	7040	4200	7203	2370	1831	4323	4300	6013
		Investment weights	0.234	0.225	0.203	0.158	0.102	0.073	0.006	0.000	0.000	0.000
			(0.101)	(0.112)	(0.110)	(0.054)	(0.021)	(-0.006)	(-0.049)	(0.000)	(0.000)	(0.000)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	7040	1303	6010	4200	6014	4082	4335	4333	4339	3040
		Investment weights	0.347	0.340	0.254	0.059	0.000	0.000	0.000	0.000	0.000	0.000
			(0.220)	(0.188)	(0.125)	(-0.050)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	7040	1303	6010	4200	4050	2100	2270	6012	4291	4014
		Investment weights	0.347	0.340	0.254	0.059	0.000	0.000	0.000	0.000	0.000	0.000
			(0.196)	(0.156)	(0.103)	(-0.060)	(-0.059)	(-0.003)	(-0.001)	(0.000)	(-0.003)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	6010	1303	4200	7203	7040	4290	1831	4015	2270	4334
		Investment weights	0.206	0.197	0.143	0.135	0.119	0.071	0.040	0.038	0.031	0.020
			(0.135)	(0.116)	(0.079)	(0.075)	(0.071)	(0.033)	(0.003)	(0.021)	(0.005)	(-0.002)
	Portfolio C (N=40)	Stock symbol	1303	6010	7203	4050	7040	1320	4290	2320	2270	4260
		Investment weights	0.203	0.197	0.129	0.109	0.106	0.067	0.066	0.053	0.033	0.024
			(0.108)	(0.114)	(0.061)	(0.052)	(0.051)	(0.021)	(0.025)	(0.000)	(0.006)	(-0.004)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	6010	1303	4200	7203	7040	4290	1831	4015	2270	4140
		Investment weights	0.215	0.202	0.150	0.139	0.123	0.072	0.037	0.034	0.029	0.000
			(0.140)	(0.118)	(0.082)	(0.077)	(0.072)	(0.032)	(-0.001)	(0.017)	(0.002)	(0.000)
	Portfolio C (N=40)	Stock symbol	6010	1303	7203	7040	4200	4050	2370	2230	4140	4323
		Investment weights	0.220	0.216	0.147	0.124	0.120	0.092	0.064	0.016	0.000	0.000
			(0.133)	(0.117)	(0.075)	(0.067)	(0.045)	(0.031)	(0.013)	(-0.003)	(0.000)	(0.000)

Notes. This table displays the top ten optimal asset allocations for strictly Shariah-adherent portfolios B and C, estimated using different investor preference models within the mean-variance optimization framework for the year 2023. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.

Table C.20: Top 10 Optimal Allocations For Moderate Shariah Adherent Estimated $\mu - \sigma$ Portfolios in 2023 - Portfolios B & C

Panel A: Classical Markowitz Model For Universe 1 (Shariah Complaint)												
Classical Markowitz Investor - No Regret	Portfolio B (N=30)	Stock symbol	1303	6010	4009	7203	7040	1320	2381	8010	8200	4161
		Investment weights	0.195	0.194	0.187	0.133	0.103	0.097	0.054	0.024	0.013	0.000
			(0.153)	(0.158)	(0.146)	(0.105)	(0.079)	(0.076)	(0.038)	(0.007)	(0.011)	(0.000)
	Portfolio C (N=40)	Stock symbol	6010	4009	1303	1830	7040	7203	2320	4142	2370	8230
		Investment weights	0.155	0.155	0.145	0.105	0.101	0.091	0.088	0.079	0.049	0.031
			(0.115)	(0.110)	(0.095)	(0.073)	(0.074)	(0.059)	(0.058)	(0.045)	(0.023)	(0.014)
Panel B: Regret Assessed Against Universe 1 (Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4009	1303	7040	8050	4142	7203	2180	3008	1213	4040
		Investment weights	0.246	0.191	0.154	0.150	0.134	0.089	0.036	0.000	0.000	0.000
			(0.188)	(0.137)	(0.117)	(0.119)	(0.094)	(0.055)	(0.028)	(-0.003)	(-0.002)	(0.000)
	Portfolio C (N=40)	Stock symbol	4009	7040	1303	6010	2370	1830	7203	4142	2320	8230
		Investment weights	0.204	0.151	0.127	0.126	0.102	0.097	0.078	0.072	0.036	0.006
			(0.138)	(0.108)	(0.064)	(0.076)	(0.058)	(0.054)	(0.040)	(0.029)	(0.003)	(-0.014)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4009	7040	1303	8050	4142	7203	4335	4240	2290	4338
		Investment weights	0.350	0.231	0.204	0.131	0.077	0.008	0.000	0.000	0.000	0.000
			(0.262)	(0.170)	(0.129)	(0.088)	(0.024)	(-0.035)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4009	7040	1303	8050	6010	2001	4002	1210	4333	2360
		Investment weights	0.333	0.229	0.202	0.123	0.113	0.000	0.000	0.000	0.000	0.000
			(0.227)	(0.157)	(0.113)	(0.074)	(0.045)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	1303	6010	4009	7203	7040	1320	2381	8010	8200	8020
		Investment weights	0.204	0.195	0.187	0.136	0.107	0.096	0.053	0.022	0.000	0.000
			(0.159)	(0.156)	(0.145)	(0.105)	(0.081)	(0.073)	(0.036)	(0.004)	(-0.001)	(-0.001)
	Portfolio C (N=40)	Stock symbol	6010	4009	1303	7040	1830	7203	4142	2320	2370	8230
		Investment weights	0.161	0.156	0.154	0.107	0.106	0.097	0.082	0.069	0.042	0.026
			(0.117)	(0.109)	(0.101)	(0.078)	(0.070)	(0.062)	(0.045)	(0.039)	(0.016)	(0.008)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	1303	6010	4009	7203	7040	1320	2381	8010	1210	6070
		Investment weights	0.206	0.199	0.194	0.137	0.107	0.093	0.043	0.020	0.000	0.000
			(0.159)	(0.159)	(0.149)	(0.105)	(0.080)	(0.070)	(0.027)	(0.002)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	6010	4009	1303	7040	1830	7203	4142	2320	2370	8230
		Investment weights	0.163	0.162	0.154	0.105	0.103	0.095	0.078	0.073	0.043	0.025
			(0.116)	(0.111)	(0.099)	(0.075)	(0.066)	(0.059)	(0.040)	(0.041)	(0.015)	(0.006)
Panel C: Regret Assessed Against Universe 2 (Non-Shariah Complaint)												
Avg. Return-regret Investor -(Alpha=0.5)	Portfolio B (N=30)	Stock symbol	4009	7040	6010	1303	1830	8311	8160	4080	2270	8170
		Investment weights	0.212	0.178	0.177	0.177	0.158	0.098	0.000	0.000	0.000	0.000
			(0.151)	(0.138)	(0.129)	(0.121)	(0.114)	(0.077)	(-0.013)	(0.000)	(-0.005)	(0.000)
	Portfolio C (N=40)	Stock symbol	4009	7040	6010	1830	1303	4142	2320	2370	7203	8200
		Investment weights	0.194	0.163	0.141	0.126	0.125	0.090	0.082	0.044	0.034	0.000
			(0.126)	(0.118)	(0.087)	(0.077)	(0.060)	(0.043)	(0.039)	(0.005)	(-0.001)	(-0.001)
Extreme Return-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	4009	7040	1303	6010	1830	4170	2140	4140	4337	4346
		Investment weights	0.334	0.274	0.171	0.159	0.061	0.000	0.000	0.000	0.000	0.000
			(0.240)	(0.208)	(0.093)	(0.091)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Portfolio C (N=40)	Stock symbol	4009	7040	1303	6010	8050	1320	3008	4260	8160	8240
		Investment weights	0.325	0.260	0.177	0.148	0.090	0.000	0.000	0.000	0.000	0.000
			(0.213)	(0.181)	(0.084)	(0.071)	(0.042)	(-0.034)	(-0.001)	(-0.004)	(0.000)	(-0.002)
Avg. Preference-regret Investor - (Alpha=0.5)	Portfolio B (N=30)	Stock symbol	1303	6010	4009	7203	7040	1320	2381	8010	8200	6070
		Investment weights	0.208	0.188	0.183	0.130	0.115	0.102	0.056	0.009	0.008	0.000
			(0.163)	(0.151)	(0.141)	(0.100)	(0.089)	(0.079)	(0.038)	(-0.007)	(0.006)	(0.000)
	Portfolio C (N=40)	Stock symbol	1303	6010	4009	7040	1830	7203	4142	2320	2370	8230
		Investment weights	0.156	0.152	0.148	0.114	0.107	0.090	0.087	0.070	0.050	0.026
			(0.103)	(0.109)	(0.102)	(0.086)	(0.072)	(0.056)	(0.050)	(0.041)	(0.022)	(0.008)
Extreme Preference-regret Investor - (Alpha=0.9)	Portfolio B (N=30)	Stock symbol	1303	6010	4009	7203	7040	1320	2381	8010	8200	8020
		Investment weights	0.207	0.190	0.188	0.131	0.114	0.101	0.050	0.010	0.009	0.000
			(0.162)	(0.152)	(0.145)	(0.101)	(0.087)	(0.078)	(0.033)	(-0.006)	(0.006)	(-0.001)
	Portfolio C (N=40)	Stock symbol	1303	4009	6010	7040	1830	7203	4142	2320	2370	8230
		Investment weights	0.153	0.153	0.150	0.110	0.104	0.088	0.085	0.077	0.053	0.027
			(0.099)	(0.105)	(0.107)	(0.081)	(0.069)	(0.054)	(0.047)	(0.046)	(0.024)	(0.008)

Notes. This table displays the top ten optimal asset allocations for moderately Shariah-adherent portfolios B and C, estimated using different investor preference models within the mean-variance optimization framework for the year 2023. The analysis is organized into three primary panels, each reflecting distinct modeling approaches and investor preference specifications. Each panel presents the stock symbols and their corresponding optimal investment weights, with parenthetical values indicating the deviations from their respective means.