Essays of Three Fundamental Biases in Behavioral Finance from the Capital Market of Bangladesh

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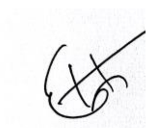
Declaration Statement

I do hereby declare that my thesis titled “Essays of three fundamental biases in behavioral finance from the capital market of Bangladesh” is the outcome of my own original research efforts, accomplished under the supervision of Dr. Mahmood Osman Imam, Professor of Finance and Dean Faculty of Business Studies, University of Dhaka.

I further declare that this research work has not been previously submitted as part of any degree requirement at this or any other university. I also declare that all sources of information have been properly incorporated by appropriate reference.
This thesis does not include any material information previously published or written by anyone except where willingly cited.

I am fully responsible and obligated for the integrity of the whole research.



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I would like to certify that my thesis title “Essays of Three Fundamental Biases in Behavioral Finance from the Capital Market of Bangladesh” has been submitted by Muhammad Enamul Haque, PhD researcher at Department of Finance, University of Dhaka as part of requirement of the degree of Doctor of Philosophy (PhD) and evaluated and approved by undersigned committee.

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Statement of Publication and Authorship

This is to inform that my Doctor of Philosophy (PhD) thesis is prepared on "Essays of Three Fundamental Biases in Behavioral Finance from the Capital Market of Bangladesh". These three biases are: the disposition effect, herding behavior, and overconfidence bias. I have already published two papers in Q2 Scopus Indexed Journals and another one is in the process of publication. The details of the publication are presented as follows:

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This paper corresponds to the Essay 1 (Disposition Effect) in the thesis.

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This paper also corresponds to Essay 3 (Herding Behavior) in the thesis.

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Abstract

The thesis empirically investigates three essays on core behavioral biases such as the disposition effect, overconfidence bias, and herding behavior within the framework of frontier equity markets like Bangladesh across distinct market states: bearish, bullish, crisis, extended crisis, and COVID-19. The developed and emerging equity markets extensively reported the evidence of biases in investor decision-making, but behavioral finance research in frontier markets remain underdeveloped and underexplored. By addressing this gap, the thesis systematically examined these three biases, applying econometric and advanced machine learning tools.

The first essay of the thesis empirically investigates whether investors have the inclination to realize the stock gains promptly rather than holding on to the stock that has declined in value under different market conditions in the Bangladesh equity market. The analysis estimates the disposition coefficients with the evaluation of the responsiveness of the current market trading volume to lagged market index prices. The findings indicate strong and ubiquitous effects of the disposition effect in the overall market and in all other markets conditions except for bearish periods. It is quite remarkable that the strength of the behavior increases in times of crisis and prolonged periods of crisis, thereby indicating that the loss aversion behavior of investors continues to increase under greater uncertainty. The results are an extension of the knowledge on behavioral trading patterns in frontier markets as they show that the disposition effect is time-varying and state-dependent. The study, therefore, adds new information on the influence of emotional and cognitive bias in the responses to the trading volume in various market setups.

The second essay discusses the nature, severity, and dynamics of herding behavior in a Bangladesh stock market in both different market states and situations. Based on the Cross-Sectional Standard Deviation (CSSD) model and Cross-Sectional Absolute Deviation (CSAD) model developed by Christie and Huang (1995) and Chang et al. (2000), respectively, in addition to a quantile regression framework, the study offers a complete picture of the investor herding concept with different market regimes. The findings demonstrate that the herding behavior in Bangladesh is widespread but also state-specific where the bearish and the protracted crisis periods depict the most prominent state-dependent herding behavior, especially in the extreme down markets. The fact that asymmetric herding happens in the high-volatility and high-trading-volume conditions supports the sensitivity of the CSSD model to explain the extreme collective movements as compared to the CSAD approach. The analysis at the industry level also shows that the herding behavior is not evenly distributed but rather concentrated in certain sectors during the periods of market stress. In addition, macroeconomic variables and monetary policy instruments have been found to have a considerable effect on herding, particularly in bearish environment, and in crisis environment. In general, the results contribute to the behavioral finance literature since they reveal the contingency of state-based, asymmetric, and policy-dependent herding behavior in frontier market setting.

The third essay explores the expression and behavior of investor overconfidence in Bangladesh stock market with a special focus on how it has been changing under different market states. The problem of overconfidence investors overestimating their ability to predict and trading too much due to the existing returns is investigated using a combined framework comprised of Vector Autoregressive (VAR), Transfer Entropy (TE), and Long Short-term Memory (LSTM) models. The analysis of the total and unexpected elements of market returns during bullish, bearish, crisis, extended crisis, and COVID-19 periods unveils that the behavioral phenomenon of overconfidence is persistent and clearly state-dependent. One of the main discoveries is a new type of behavior, which is called defensive overconfidence: when the market is under intense stress, especially in equity market downturn, investors still show overconfident behavior, yet their behavior corresponds to defensive responses to uncertainty, instead of optimism of making future gains. The analysis at the industry level also proves the prevalence of this bias in all major and dominant industries. Overall, the findings are expected to make contributions to the behavioral finance literature by adding a new conceptual dimension to the notion of overconfidence, as well as evidencing the applicability of hybrid econometric-machine learning paradigms in order to capture the non-linear and adaptive nature of investor psychology in frontier markets.

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Chapter One: Introduction

1.1 Background of the Thesis

Behavioral finance, which came forth as a distinct field of study, challenges the investment decision-making framework observed in traditional rational financial models since its inception in the late 1980s, in particular, with the work of Daniel Kahneman and Tversky (1979). Classical finance theories mainly evolve around the Efficient Market Hypothesis (EMH), which builds on the presumption that equity market investors always behave rationally and make consistent decisions that optimize their economic prosperity. But real financial markets often present a different story. Investors do not always behave rationally; rather, their investment decisions are strongly influenced by psychological factors and cognitive limitations. This is how behavioral finance develops as an alternative to rational investment framework. These behavioral patterns lead investors to make systematic errors in their thinking ability, causing the securities prices to deviate from the intrinsic values.

Among the most widely empirical investigation of behavioral biases in the equity market are the disposition effects, herding behavior and overconfidence bias. These behavioral biases are especially prevalent in the equity markets, where information is asymmetric, and a large number of retail investors engage in trading without formal education or access to modern investment tools.

The study of these biases has become pragmatic or even more critical in the context of frontier equity markets like Bangladesh. The country's two main bourses: the Dhaka Stock Exchange (DSE) and the Chittagong Stock Exchange (CSE), have experienced rapid growth in terms of both market capitalization and in the number of active investor participation over the last two decades. Retail investor dominance, political instability and experience of extreme market volatility- a massive market crash happened in 2010-11, raise concern about the significance of irrational behavior of investors in equity price movements and market dynamics.

Despite the significant development of the Bangladesh equity market, there is limited exploration of research in behavioral finance. This uniquely represents a significant gap in studying investor psychology. Most of the empirical studies in behavioral finance mainly concentrated on developed and emerging equity markets. A very few studies have investigated behavioral biases in frontier equity markets setting. Behavioral biases should be studied in a frontier market, like Bangladesh, which has the benefit of offering an environment with a rich structure and institutional characteristics. The theory of behavioral finance assumes that irrationality is more apparent when market frictions, information asymmetry and speculative trading prevail in the decision-making process (Barberis & Thaler, 2003). The frontier markets are usually under covered by analysts, low liquidity, poor corporate governance, and are dominated by retail investors who do not make decisions based on fundamental analysis. These attributes enhance behavioral biases like the disposition effect, overconfidence and herding. As an example, the thin trading and slow information flow may induce investors to trust recent market data, which leads to herding, and the absence of professional mediation may strengthen the overconfidence and disposition biases. Thus, theoretically, the structural inefficiencies and investor structure of frontier markets provide good soil where the behavioral biases can be expressed and perpetuated.

By motivating this gap, the research intends to empirically investigate three fundamental behavioral biases, such as the disposition effect, herding behavior, and overconfidence bias, within the framework of the Bangladesh equity market. The research is structured into three standalone essays, each explaining one of these biases to measure their presence and significance for our equity market. The main objective is to contribute to growing behavioral finance literature by exploring insights specific to a frontier equity market and providing evidence in support of decision-making for market participants and policymakers in the Bangladesh equity market.

1.2 Significance of the study

This thesis possesses remarkable importance for academic research by observing anomalies in the Bangladesh equity market and offers practical implications for the equity market investors, regulators, and policymakers. From an academic standpoint, the research advances behavioral finance literature by furnishing empirical observations from an under-researched, and behaviorally unexplored frontier equity markets like Bangladesh. Bangladesh equity market makes an ideal ground for examining behavioral biases because its market characterization significantly differs in terms of market depth, regulatory framework, investor sophistication, political environment and access to information. The study explores extending current knowledge by examining the three fundamental behavioral biases under the challenge of socio-economic and institutional equity market dynamics. Each essay within these biases adds value to the existing body of knowledge development by adopting econometric, information-theoretic entropy models, and machine learning tools, while capitalizing on aggregate market-level data and systematic robustness to validate research's empirical findings.

From a practical implication aspect, the research brings the potential to improve the decision-making capability of individuals and other market participants by emphasizing the common psychological limitations they may encounter. Understanding and analyzing these behavioral biases can promote better equity market investment behavior, reduce excessive trading, mitigate market volatility and encourage more rational financial decision-making. Furthermore, the research may guide and help market regulators and policymakers including the Bangladesh Securities Exchange Commission (BSEC) and the Dhaka Stock Exchange (DSE), in assessing the behavioral tendencies of market participants that shape equity market dynamics.

Assessing the presence and intensity of these behavioral biases may assist policymakers in formulating strategies that can minimize irrational investor behavior by enhancing market transparency, promoting investor education, and reinforcing other financial literacy programs that underscores its behavioral consequences.

1.3 Research Problem and Question

Despite the widespread progression of behavior finance since its inception in the early 1990s, the most empirical studies have concentrated on developed and emerging economies where equity market data is more structured and available. As a frontier equity market, Bangladesh is more vulnerable to equity market inefficiencies and exposure to behavioral biases due to its structural and behavioral characteristics. But the research on behavioral finance remains at an early stage in Bangladesh, inducing an ideal ground for studying these behavioral biases. This limited attention raises the core research problem this thesis addresses- how, and to what extent, behavioral biases shape investment behavior of market participants and impact market dynamics within the framework of frontier equity markets like Bangladesh.

Given the background, the thesis addresses the following research questions related to each behavioral bias:

Research Question 1: Is the disposition effect prevailing in the bearish and bullish market phases in the equity market of Bangladesh, representing how investors intend to sell their winning stocks promptly, while holding on to losing stocks too long under different market conditions?

Research Question 2: Does overconfidence bias appear in the Bangladesh equity market, analyzing that total and unexpected market returns can significantly predict trading volume across diverse market states?

Research Question 3: Do equity market investors in Bangladesh exhibit herding behavior and how does the nature, direction and herding intensity differ asymmetrically under different market conditions and across distinct market states?

Motivated by these research questions, the thesis formulates the specific research hypotheses to systematically investigate each behavioral bias in the Bangladesh equity market, with respective chapter explaining and empirically testing each bias separately.

In addition to scholarly investigation, the knowledge of the biases in behaviors has significant policy implications for the frontier markets. In Bangladesh, retail investors form the largest market participants and the occurrence of speculative bubbles, and the bursts has been a regular destabilizing factor on investor confidence and the market stability. Determining the behavioral patterns that underlie such anomalies, this research offers insights that can be used in investor education initiatives, enhance disclosure and governance standard creation, and inform the creation of behaviorally aware regulatory frameworks. Further, as Chapter Six addresses, the interplay between macroeconomic policy change and herding behavior has implications on the monetary authorities, and it is likely that communication policies should be employed to reduce the irrational market responses to a policy change. Therefore, this thesis not only provides a contribution to behavioral financial literature, but also to creation of more resilient and psychologically sensitive financial policies in emerging and frontier economies.

1.4 Brief Overview of Three-Essay

The thesis embraces three essays on fundamental behavioral biases in which each essay describes a self-explanatory systematic analysis of investors' psychological behavior within the context of frontier equity markets such as Bangladesh. Each essay is structured and presented with its own theoretical underpinnings, review of literature, methodological framework, empirical findings and discussion, and conclusion. These three-essay analysis collectively provide significant contributions to behavioral finance by exploring how investors' psychological and cognitive behaviors shape their investment decisions in the Bangladesh equity market.

Essay one: Disposition Effect

The first essay focuses on the disposition effect, which represents the tendency of investors to realize the winning securities quickly and retain the losing securities for longer periods. This behavior represents a deviation from the traditional rational expectation model, which can result in suboptimal investment decisions. Empirical studies have documented that such irrational behavior of investors is significantly influenced by the psychological factors that can be explained by the classical financial models. This evidence is widely present in developed and emerging equity markets; the frontier markets like Bangladesh may exhibit different behavioral patterns due to investor sophistication, lower market depth, and liquidity.

Essay Two: Herding Behavior

The second essay investigates herding behavior, a behavioral tendency of equity market investors to replicate the actions of major market players, neglecting their own private analysis or beliefs. This behavior represents the correlated investment decision-making that cannot be justified by underlying investment fundamentals. Using aggregate market-wide and industry-level data, the essay examines how investors in the Bangladesh equity market tend to follow market trends across diverse market states such as bearish, bullish, crisis, extended crisis, and COVID-19. The essay demonstrates a comprehensive examination of whether the investor herding tendency amplifies during periods of market volatility and heightened uncertainty, promoting the level of market inefficiency.

Essay Three: Overconfidence Bias

This essay examines overconfidence bias, where investors overestimate the precision of their skills, judgment, or predictive capabilities regarding future market movements. The puzzle of overconfidence is tested by analyzing whether past market returns (assessing both total market returns and the unexpected component of market returns) can predict market trading volume across different market states. Overconfident investors often engage in excessive trading, which may lead to mispricing of securities. This bias challenges the assumption of traditional rational financial decision-making models and may exacerbate the equity market volatility within the market setting of thinly traded frontier markets. In addition to the examination of investors' overconfidence at market level, the essay expands the focus on the industry-level data to provide deeper insights into how investor psychology varies across different industries.

As behavioral finance has been widely examined in both developed and emerging markets, only few studies have been conducted on the frontier markets. The capital market of Bangladesh has been experiencing a high growth rate, and the volatility is intermittent in processes and has seen the changing institutional arrangements, and thus, it is a good place to experiment whether the behavioral theories that were developed in the mature market apply in other structural and cultural environments. Investor behavior has been found to be different based on institutional maturity, financial literacy and regulation of the market across countries (Cross country studies by Chui et al., 2010; Kim and Nofsinger, 2008). This study adds to world comparative finance literature by extrapolating the behavioral analysis to Bangladesh by showing how the tendencies to behavior change in response to informational and institutional realities of frontier economies. The results, therefore, provide an insight into the gap between the theoretical constructs based on the mature markets and the behavioral aspects of the markets that are in the initial phases of their development.

1.5 Thesis Organization

The thesis is structured as follows:
Chapter 2 presents the overall literature review on three behavioral biases; chapter 3 presents the general methodological framework and data sources; chapter 4 describes the first essay on the **Disposition Effect**; chapter 5 details the second essay on **Overconfidence Bias**; chapter 6 explains the third essay on **Herding Behavior**; and chapter 7 summarizes and synthesizes the thesis findings across these three essays.

Chapter Two: An Overview of Literature Review on Three Behavioral Biases

2.1 Introduction

The existing literature furnishes the foundation of this research, positioning the three biases within the broader empirical framework of behavioral finance research. Classical financial theories presume rational investor behavior having perfect information. However, evidence indicates that investors often behave in ways that deviate from rationality. These systematic deviations from intrinsic values, known as behavioral biases, may significantly impact investors' decision-making, securities pricing, and equity market dynamics.

Many empirically evident behavioral biases impact financial decision-making, but three fundamental biases have gained particular attention to academic research: the disposition effect, herding effect, and overconfidence bias. Each of these biases suggests a systematic tendency in judgment and decision-making to challenge the notion that investors are fully rational, and markets are efficient. Behavioral biases are particularly important in frontier markets like Bangladesh, where retail investors dominance, weak regulatory frameworks, and information asymmetry may amplify them. The objective of this chapter is to review the existing literature relevant to the three biases examined in this thesis. The literature is organized into three main segments. First, we present the disposition effect, highlighting how investors intend to sell winning stocks prematurely while holding on to losing ones. Herding behavior is described in the second part, which highlights how investors imitate the actions of others, ignoring their own analysis. In the third part, we explain overconfidence bias, which states the overestimation of the investor predictive ability about future trading volume based on the past market information.
This literature part has twofold motivations. First, it provides a general overview of the empirical developments surrounding these three biases across the global equity markets. Secondly, it identifies gaps in the existing literature that the present thesis seeks to address, providing the motivation for the subsequent empirical essays.

2.2 Behavioral Transmission Mechanisms and Theoretical Underpinnings

Behavioral biases function on a well-established psychological level, which distorts rational decision making and when combined, creates market inefficiencies.

Disposition effect: Prospect theory, and regret aversion theories explain this effect where investors consider the pain of losses more than gains of the same magnitude, believing them to hold losing trades and sell winning positions promptly. This attitude slows down the speed of price change and results in momentum shifts in the frontier market.

Overconfidence bias: Investors have overconfidence and illusions of control, which leads to a high level of trading and volatility. This bias is enhanced in such markets as Bangladesh with little known information and speculative trading where individual overreaction is associated with systemic volatility.

Herding behavior: Herding is an action that is explained by informational cascades and social conformity, whereby investors follow other investors in their actions when they lack certainty.

This group think increases market booms and busts particularly in markets that are dominated by information asymmetry and noise trading.

Such theoretical processes relate investor psychology with quantifiable inefficiencies, establishing the behavioral basis of the empirical results of the subsequent chapters.

2.3 Empirical evidence on Disposition Effects

2.3.1 Disposition effect

The disposition effect is the tendency of equity market investors to sell the winning securities too early and hold on to the losing securities for longer periods. Many studies have empirically investigated the disposition effect in various equity markets to measure its presence and determinants depending on investor type or investors' demographic characteristics. This part of the chapter presents a general description of these empirical studies examined on the disposition effect bias in the equity markets.

Shefrin & Statman (1985) first developed the theories to explain why the disposition effect exists in the equity market such as prospect theory, mental accounting, regret aversion. Odean (1998) empirically investigated the disposition effect in the US equity market showing that investors have strong preference for selling the profitability stocks more quickly than the losing stocks. Shaperia & Venezia (2001) confirmed that individual investors do exhibit strong disposition effect than the professionally managed fund managers in the Israel equity market. Barberis & Xiong (2009) demonstrated that realized gains or losses model of prospect theory preferences better predict the disposition effect than the annual gains or losses preference model.

Frino, Lepone & Wright (2015) confirmed the robust evidence of the disposition effect in the Australian equities market across different investor levels, and it was more prominent with women, and investors having Chinese background. Zahera & Bansal (2019) evidenced from a systematic literature review of research articles over a period of 35 years that individual investors are more likely to display the disposition effect where institutional investors may or may not exhibit this bias. Oreng, Yoshinaga, & Eid (2021) revealed that the presence of the disposition effect in Brazilian equity market varies depending on investor sophistications, gender, age, and even the market conditions: bullish or bearish. Sadhwani & Bhayo (2021) showed that momentum does not influence the disposition effect, but the size and the disposition effect can drive momentum in the US equity market.

Favreau & Garvey (2021) evidenced that corporate insiders exhibit the disposition effect but are more willing to buy stocks whose value has decreased compared to those that have increased. Kiky (2023) analyzed the theoretical and bibliometric evidence on the disposition effect and demonstrated that the prospect theory is the dominant cause to explain the disposition effect phenomenon in the equity markets. Dorn & Strobl (2023) argued that the disposition effect can help investors to design trading strategies in the German equity market when information asymmetry is reduced. An Engelberg, Henriksson, Wang, & Williams (2024) investigated the portfolio-driven disposition effect in the US and China and confirmed that the disposition effect becomes stronger when the portfolio is in a loss rather than in a gain position.

By combining these studies, it is observed that the disposition effect is a strong effect in various market situations, which varies in intensity and prevalence depending on market structure and the investor types. Majority of the evidence is found in developed and emerging markets, where dissemination of information and institutional oversight decrease the irrationality of trading. The opposite is true with frontier markets such as Bangladesh, which have lower liquidity, fewer professionals and less information efficiency, which makes it a stronger environment to experience loss aversion and regret-based decision making. Therefore, the theoretically more pronounced disposition tendencies of investors in Bangladesh are prone to be, particularly, in the circumstances of trading in volatile and sentiment-based conditions.

2.3.2 Herding Behavior

Herding behavior refers to the tendency of market particpants to imitate the collective market behaviors sacrificing their private knowledge or information. This behavior can contribute to mispricing, which collectively results in the equity market volatility. This part provides a brief overview of empirical studies on herding behavior, focusing on how various reserachers have investigated and evident its presence across different equity markets dynamics.

Christie & Huang (1995) were the pioneers to test empirically market-wide herding behavior in the US equity market and found no evidence during periods of extreme market movements. Chang et al. (2000) investigated equity markets of US, Japan, Hong Kong, China, Taiwan and South Korea and reported the strong herding behavior from the two emerging markets of Taiwan and South Korea. Herding behavior was absent in the Mediterranean equity markets of Spain, Italy and Greece but was present in Portuguese market (Economou et al., 2011). Chiang et al. (2010) found no herding behavior for B-share markets, but it was evident for A-share markets from both Shanghai and Shenzhen equity markets in China.

Prosad et al. (2012) and Poshakwale & Mandal (2014) documented market-wide herding behavior in the Indian equity market. Adam (2020) confirmed the strong presence of herding in Istanbul equity market during up market compared to down market. Vo & Phan (2017) found that herding behavior was more robust during pre-crisis, crisis, and post-crisis in the Vietnam equity market. Chaffai & Medhioub (2018) showed that herding behavior was present only during up market in Islamic Gulf Cooperation (GCC) equity markets. Indras et al. (2019) found herding behavior in the Moscow equity market under certain market scenarios such as during oil price changes, macroeconomic news releases. Herding behavior was strongly observed in the Singapore equity market at both portfolio and aggregate market level (Arjoon et al., 2020). Jiang et al. (2021) reported the clear evidence of herding during the COVID-19 pandemic in six Asian equity markets of Japan, China, Hong Kong, South Korea, Singapore, and Taiwan. Jirasakuldech & Emekter (2021) stated that investors in the Thailand equity market exhibited herding behavior during the periods of substantial trading volumes, the 1997 Asian crisis, and economic downturns.

Maquieira & Espinso Mendez (2022) evidenced herding behavior in the Chinese equity market with more pronounced after the COVID-19 shocks. Bogdan et al. (2022) confirmed that herding behavior is more prevalent in emerging equity markets compared to the frontier and developed markets. Shrotryia & Kalra (2022) revealed that the US equity market does have significant influence on herding tendencies of investors in BRICS markets except for China. Ampofo et al. (2023) documented evidence of herding behavior in bullish markets during COVID-19 in developed equity markets of US and UK but not found in bearish markets of both countries.

Hasan et al. (2023) showed strong evidence of herding in 33 global equity markets during different crises periods like the Euro Zone, aftermath of Brexit, and the COVID-19. Hakmaoui & Jabari (2023) did not find herding behavior in the French and the Tunisian equity markets but found the evidence for the US and Morocco, demonstrating that herding was more prominent in frontier markets compared to the developed equity markets. Metawa et al. (2024) found herding in the Egyptian mutual funds only in down market condition during both the pre-COVID-19 and post-COVID-19 regimes. Dhuri & Patkar (2024) showed that herding behavior was present in the Indian equity market under the conditions of structural breaks and high trading volumes. Nguyen and Vo (2024) confirmed the evidence of herding in the Vietnam equity market only after the post-COVID-19 but not for during or before COVID-19. Yahya et al. (2024) identified that firm size, exchange rates, and market volatility can significantly influence herding behavior in the Jakarta Islamic Index. Medhioub (2025) revealed that herding behavior prevails in all MENA equity markets except for Lebanon in a down market. They also mentioned that geopolitical risk has some influence on herding behavior especially in Jordan and Tunisia.

Given the experience of global equity markets, it indicates that overconfidence is sometimes driven by the investor believing that his ability to succeed, and underestimating chance, which creates excessive trading, and return-volume feedback loops. In frontier markets where speculative trading is a large part of the market and the quality of disclosure is worse, investors base their trading decisions relying on personal judgment rather than fundamentals, amplifying overconfident behaviors. Thus, the Bangladesh equity market presents a perfect experimental environment to study how the effect of market state dynamics including the bullish and the bearish markets, improve or curb an overconfident behavior of the retail-dominated investors.

2.3.3 Overconfidence

Overconfidence, one of the well-documented behavioral biases, has been extensively studied in developed and emerging equity markets, but the frontier markets remain underexplored. This section presents an overview of empirical research that investigated overconfidence bias across different equity markets, hypothesizing that past market returns can predict future trading volume.

Staten (2006) empirically evidenced the presence of overconfidence bias in the US equity market where it was more observed in small-capitalized stocks relative to large-cap stocks. Chuang & Lee (2006) confirmed the acceptance of overconfidence hypothesis, stating that investors overreact to private information and underreact to publicly available information in the US equity market. Metawally & Darwish (2015) showed that investors in the Egypt equity market are overconfident, examined in both positive and negative trend volatility conditions. Trinugroho and Sembel (2011) proved through an experimental research that overconfident investors engage in excessive trading and generate lower returns in the Indonesian equity market. Zia, Sindhu & Hashmi (2017) discovered that past market returns have positive associations with future trading volume in the Pakistan equity market, supporting the existence of overconfidence bias.

Mushinda & Veluri (2018) documented investors' overconfident behaviors in the Indian equity market, which was mainly driven by self-attribution theory. Soleman and Omar (2020) found that investors in the Saudi equity market exhibit overconfidence bias in their investment decisions. Mushinda & Veluri (2020) found robust evidence of overconfidence bias during both pre-crisis and post-crisis environments in the Indian market. Shrotryia & Kalra (2021) did not find overconfidence in developed equity markets but found its presence in the equity markets of China, Taiwan, Jordan, Turkey and Vietnam during COVID-19 phase.

Findings from the study of Alsabban & Alarfaj (2020) evident the lead-leg relationship between market return and trading volume indicating the existence of overconfidence bias in the Saudi equity market. Kuranchie-Pong & Forson (2022) indicated that overconfident behavior has significant influence on weekly volatility in the Ghana equity market, especially, during the COVID-19. Azam et al. (2022) showed the evidence of overconfidence bias for cyclical industries during and the pre-COVID-19, but not for defensive industries in the Indian equity market. Bouteska et al. (2023) documented that overconfidence was present among investors in the US equity market. Ganesh et al. (2022) found overconfidence bias in the Indian equity market during the 2007-2008 financial crisis and COVID-19 pandemic. Kumar & Prince (2022) also reported the evidence of overconfidence bias during pre-market crash but did not find any evidence from post-market crash in the Indian equity market.

Existing studies point to the conclusion that herding behavior is dependent on the market and market stress conditions. Given that there is limited herding in developed markets with respect to advanced institutional trading, an emerging or frontier market tends to exhibit more significant herding pattern, especially at crisis times or at times of uncertainty. Since a significant percentage of retail investors present in Bangladesh, the lack of transparency of information, and the openness to both policy and political shocks, herding is theoretically supposed to be a more constructive influence of market-wide co-movements, which contribute to mispricing and volatility.

2.4 Synthesis of Inconsistencies and Methodological Justification

Despite the consistency in the findings of the studies that have been conducted, the relevance of behavioral biases has not been determined irrespective of markets, time and empirical methodologies. The thesis indicates that some studies have high disposition and herding effects when there are bullish situations and others in crisis or bearish situations. On the same note, evidence of overconfidence differs based on market conditions (volume-return causality, volatility patterns or trading frequency). These inconsistent behaviors represent the significance of market structure, investor composition, and macroeconomic environment on behavioral phenomena.

In order to fill these gaps, the current thesis presents a few innovative methodological approaches: Dow Theory as a classification of market states, application of quantile regression and VAR approaches to incorporate nonlinear and state-dependent dynamics and integrating macroeconomic and monetary policy variables in herding dynamics. These methodological advancements help understand and explore the complex, context-specific perspective on behavioral biases in a frontier market context

The thesis contributes to the advancing body of behavioral finance research by systematically providing empirical evidence on three fundamental behavioral biases such as the disposition effect, overconfidence bias and herding behavior in the context of Bangladesh capital market. Being a frontier market structurally characterized by liquidity constraints, high uncertainty, less participation of institutional investors, and political instability, the Bangladesh equity market provides an ideal ground where behavioral biases are more likely to prevail compared to the developed and emerging market environments. By classifying the market into different states, including bearish, bullish, crisis, extended crisis, and COVID-19, the thesis strengthens the understanding of how investors' psychology responds to these behavioral biases under market states dynamics. The bullish and bearish market trends are determined by applying Dow Theory, which is an innovative methodological development in existing literature. Findings intend to expand global development by highlighting the insights within a frontier equity market setting, which largely remain underexplored in behavioral finance literature.

Chapter Three: General Methodological Framework for Three Behavioral Biases

3.1 Introduction

This chapter begins with the description of the methodological approaches employed to investigate the three core and prominent behavioral biases such as the disposition effect, overconfidence bias and herding behavior, in the Bangladesh equity market. The choice of methodology is logically determined by the unique structural characteristics of the Bangladesh capital market, which are aligned with the overall research objectives developed in the introduction chapter and the research gaps uncovered in the literature review in chapter 2.

This thesis is framed around three standalone essays, each focusing on a distinct behavioral bias in the equity market, necessitating a multi-dimensional aspect. An integration of statistical, econometric, and machine learning models has been adopted to effectively capture how the variations of investor psychology better fit to individual behavioral biases.

The methodologies are presented in this chapter at the general level, showcasing their relevancy, rationale, and appropriateness. Whereas the empirical model specifications. Including the equations, variables, indicators of bias presence, and robustness checks, are described in detail in the respective behavior bias essay chapters. This organization facilitates both consistency and coherence throughout the thesis and provides a detailed technical understanding in each essay.

3.2 Research Philosophy

This thesis applies a quantitative approach, which is aligned with the positivist research paradigm. It refers to a philosophical viewpoint in empirical research in which investor behavior (a psychological phenomenon) in financial markets can objectively be measured and quantified by analyzing financial data. Behavioral finance concentrates on identifying and understanding systematic deviations observed in equity market behavior that cannot be explained by rational financial models. As a result, the thesis strives to empirically investigate the three fundamental behavioral biases, such as the disposition effect, overconfidence bias, and herding behavior, in the Bangladesh equity market.

The thesis adopts a deductive research approach, which originates from the established theories and empirical findings in behavioral finance literature and then validating their presence against real financial market data. By blending the statistical, econometric, and information-theoretic approaches along with deep learning tools, the thesis comprehensively examines whether these behavioral biases explicitly evident in developed and emerging economies are prevalent in the Bangladesh equity market and how they display across different equity market states.

The quantitative methodology is well-suited to examine these behavioral biases because it facilitates the rigorous analysis of investors' behavioral tendencies using equity market data, recognizing causal or predictive relationships, which enables the assessment of variations across distinct market states. Moreover, the employment of a wider spectrum of methodologies spanning from linear econometric models to non-linear, non-parametric information theoretic approaches to the cutting-edge advanced machine learning models, strengthens the robustness and consistency of the research empirical findings.

3.3 Data and Sample

For this thesis, the dataset consists of daily closing prices as well as trading volume for all stocks available on the Dhaka Stock Exchange (DSE) in Bangladesh. Securities prices are adjusted to incorporate the effects of dividends, bonus shares and other corporate actions. For the disposition effect, the data period includes from January 1, 1993, to December 31, 2020; whereas for herding behavior and overconfidence bias, the data period spans from January 1, 2010, to December 31, 2021. We constructed equally weighted aggregate market returns by averaging individual returns of all stocks traded on each day, equally weighted industry market returns, aggregate trading volume by summing the individual trading volume of all securities traded each day, and industry trading volume. We also constructed unexpected equally weighted aggregate market returns extracted from the Market Index model. The thesis classifies the whole study period into bullish, bearish, crisis, extended crisis, and COVID-19 to understand and capture how behavioral biases differ across these market states. In addition, to analyze the effects of macroeconomic shocks and the monetary policy shifts on herding behavior, the thesis considers the data of exchange rate, interest rates, deposit rates, deposit reserve ratio over the period 2010-2021. These data were collected from the annual report of the Bangladesh bank.

3.3.1 Data Cleaning and Transformation for Reproducibility

A systematic data cleaning and transformation protocol was adhered to in order to guarantee reproducibility. Calculation of adjusted closing prices was done to indicate corporate activities such as cash dividends, bonus issues and rights shares. Both the z-score and percentile-based trimming were used to identify an outlier to reduce distortions due to illiquid stocks. The data on trading volumes were normalized by the outstanding numbers of shares to make the data comparable between the firms. They were then constructed as aggregate and industry level indices by taking equal weighted averages so that no individual firm operated as the dominant company in the index. Lastly, all the computations were made with reproducible scripts in R and Python which meant that it is possible to have a transparent replication of the process of data generation and transformation.

3.4 General Methodological Framework

This section outlines the general description of specific methodologies implemented across behavioral biases examined in this thesis. The detailed empirical model specifications of each approach, including technical aspects, variable identification, estimation process, hypothesis development, and bias detection strategies, are provided in the respective chapters presenting each behavioral bias.

The thesis attempts to apply the diverse empirical methodologies to investigate the three core behavioral biases like the disposition effect, overconfidence bias and herding behavior, in the Bangladesh equity market. Each behavioral bias possesses a specific aspect of investors' behavioral tendencies and thus necessitates a diverse methodological application for its precise measurement.

3.4.1 Disposition Effect

The disposition effect occurs when equity market participants have the tendency to sell their winning stocks hastily while retaining the losing stocks for a longer period. Most of the empirical studies measured the disposition effect adopting the Odean (1998) framework, which can be defined as the proportion of gains realized (PGR) to the proportion of losses realized (PLR). This measure analyzes trading records to understand how investors treat their investments that have gained in value relative to those that have declined. If there is a consistent pattern observed for realizing gains more often than realizing losses, it confirms the evidence of the disposition effect in the equity market.

This thesis determines the disposition effect by applying Weber and Camerer's (1998) alpha approach, which was also used by Hermann et al. (2019). In their calculation of the disposition coefficient, they considered the representation of the previous day's market prices as a benchmark. But this thesis replaces the previous day's market price with the market index. To calculate the disposition coefficient, the research incorporates how today's trading volume is influenced by the direction of the market return of the previous day. The statistical significance of the disposition coefficient is tested by the distributional or parametric test, like the t-test, and proportion (Z test), while the Wilcoxon rank sign test is used as a non-parametric test.

3.4.2 Herding Behavior

Herding behavior in equity market refers to investors' intensity to follow the collective market trends or the actions of other investors overlooking their own private analysis or investment fundamentals. The thesis utilized Christie and Huang's (1995) original cross-sectional standard deviation (CSSD) and Chang et al. (2000) cross-sectional absolute deviation (CSAD) models to empirically examine herding behavior in the Bangladesh equity market. These well-established CSSD and CASD framework test whether investors imitate the market consensus in their investment decisions under different market conditions, such as up and down markets, high and low trading volume, and high and low market volatility across distinct market states, including bearish, bullish, crisis, extended crisis, and COVID-19. Both the models are also modified to explore how herding tendency may vary during extreme market returns, extreme trading volume and extreme market volatility phenomena. To ensure the robustness of the research findings, the thesis further incorporates the quantile regression approach to explore the heterogeneity in herding tendency across different phases of return distributions.

3.4.3 Overconfidence Bias

Understanding the complex nature of investor behavior and market dynamics, the thesis examines overconfidence bias by applying traditional econometric vector autoregressive (VAR), an information-theoretic transfer entropy measure, and a Long Short-Term Memory (LSTM) machine learning model. These three methodologies test overconfidence bias by focusing on whether the total market returns, as we as unexpected market returns, can predict trading volume across different market states to detect the presence of the bias.

Vector Autoregressive (VAR) is a linear econometric framework widely used in herding literature to analyze interdependencies between aggregate market returns and trading volumes. This approach measures how past market returns can influence trading volumes through the statistical significance of lag market returns, an indicator of overconfident behavior in the equity market.

Transfer Entropy is a non-linear, asymmetric, and non-parametric approach capable of capturing true directional causality between two financial time series. It quantifies how much knowing the past market return information reduces significant uncertainty about predicting trading volume. The statistically significant transfer entropy coefficient indicates that flow of information is transferred from market returns to trading volume, supporting the overconfident trading behavior in the equity market.
Long Short-Term Memory is a special variant of recurrent neural networks, which learns patterns by modeling non-linear, complex, delayed sequential behavior specially designed to capture long-term dependencies in investor behavior. This deep learning model is particularly applicable for sequential financial time series data to detect temporal dependencies and predictive behavioral patterns, which traditional models may fail. The LSTM uses a multi-layer estimation process, comprising of input layer, LSTM layer and output layer. The model predicts trading volume built on its two model versions: the Baseline (that includes only past trading volume) and the Restricted model (that includes both past market return and trading volume). The lower mean squared error (MSE) of the Restricted model implies that past market returns contain significant information to predict future market trading volume, an indication of the presence of overconfidence bias.

The integration of traditional econometric vector autoregression (VAR) with informatic transfer entropy measures and cutting-edge deep learning models provides a multifaceted nature of overconfident behavior in the Bangladesh equity market across diverse market states and strengthens the robustness of the research's empirical findings. Furthermore, the application of this multi-method framework significantly contributes to the expanding behavioral finance literature.

These behavioral biases are examined with a diverse methodological innovation exclusively focusing on secondary equity marker data rather than subjective human characteristics. Therefore, the ethical considerations are acknowledged by complying with the principles of integrity and honesty in academic research.

3.4.4 Robustness and Model Validity

In order to guarantee reliability and validity of the empirical findings, several robustness and validation processes were followed in the various behavioral models.
Model robustness: Behavioral biases have been tested on both parametric and non-parametric tests where necessary. For example, the disposition effect was confirmed by t-tests and non-parametric Wilcoxon tests, herding was re-estimated under quantile regression to test asymmetry

of effects across return distributions and overconfidence results were cross-validated among linear and non-linear frameworks, i.e. econometric (VAR), information-theoretic (Transfer Entropy) and deep learning (LSTM).

Stability checks: The temporal stability was assessed by conducting sub-period analysis under various market states (bullish, bearish, crisis, extended crisis, and COVID-19) to evaluate the stability of the various time conditions. The presence of several market phases eliminates the possibility of the results being prejudiced by certain periods or drastic circumstances in the market.

Model diagnostics: VAR framework provides standard residual diagnostics, and lag-length diagnostics (autocorrelation, stability, and normality tests). LSTM analyzes the performance of the model through train-test split validation and comparing mean squared error (MSE) between the baseline and restricted models.

Reproducibility controls: Standardized financial data transformations, equal frequency (daily), and standard descriptions of variables were used to estimate all empirical models such that the results can be compared directly across methodologies.

3.5 Determination of Bearish and Bullish Periods using Dow Theory

The thesis applies Dow Theory to identify the bearish and bullish segments of the Bangladesh equity market, a novel contribution to behavioral finance research. Dow theory named Charles Dow in the late 19th century and is considered the father of technical analysis.

3.5.1 Rationale of Dow Theory

Considering both theoretical and practical reasons the thesis has chosen Dow Theory as the classification of market states. In theory, the Dow Theory is a price-following, trend-following model that can explain long run investor sentiment and structural reversals in equity markets without relying on arbitrary levels or macroeconomic indicators. Dow Theory is based on pure price moves and trend confirmation by investors unlike the other segmentation techniques (volatility-based regimes, Markov-switching models, or fixed-percentage rules (e.g., a 20-percent upside downside range to designate bull- or bear-related price moves). This is what makes it especially suitable in frontier markets such as Bangladesh, volatility there can also be quite common and not necessarily indicative of long-term directional movement. In addition, the trend confirmation that Dow Theory depends on regarding successive higher highs and lower lows is very consistent with the principles of behavioral finance since it is a way of tracking the way masses of investors feel about something over time. Therefore, this method guarantees objective, transparent and behaviorally consistent grouping of bullish and bearish market conditions, which are necessary to examine psychological biases in various conditions in the equity market.

The theory states that there should be three fundamental forms of trend observed in the equity market: primary, secondary, and minor trends. The primary or major trend is the substantial positive and negative movement of the market that lasts for more than a year and may continue for several years. Thus, any pattern of the trend, whether it is bullish and bearish, may continue over a long period is known as the primary trend. Secondary trends are the swings of the market that are traced out in interrupting the movements in direction of the primary trend; a phenomenon of reactions that suspend the smooth progress of the movements of primary direction. These secondary trends are termed as corrections or intermediate declines for a bull market, and it is termed as reactions or intermediate rallies for a bearish market. The duration of secondary trends varies from three weeks to three months. The retracement of the secondary trend happens at a minimum of 33 percent to a maximum of 66 percent of the previous net progress of the primary trend. A minor trend is the short-term movement of the market that lasts for one day to three weeks.

Dow Theory adopts a distinct procedure to recognize the bearish and bullish periods of the equity market. A bullish trend is identified when each successive price movements reflect higher highs or lower lows for a prolonged period. On the other hand, a bearish market is determined where repeated price changes show lower highs or lower lows persist for a sustained period relative to previous price changes.

In every primary trend, there are three phases recognized. During the first phase of accumulation or consolidation, farsighted investors will start buying the stock apprehending that businesses would gradually turn up. Prices do not change significantly because they are the minority group to influence the overall market movement. In the second phase of public participation, general investors enter the market in response to realizing the fact that improvement of good news is coming out and everybody has a positive perception about corporate earnings as well as the movement of the aggregate market. Prices massively jump at this stage against the backdrop of public participation. Analysts will come to frame towards the end of the public participation phase and perceive that the abnormal earnings condition of the corporation might not sustain in the future. Selling pressure will be induced by them and the market will observe the first move of a downtrend. Once the non-sustainability of excess earnings is confirmed by mass participants, the market experiences the second move down. Investors will become panicky and more distressed sales will lead to an acceleration of vertical drop. After this extreme fall in prices, reconstruction will begin once again when astute investors make an entry for consolidation.

The below Table 1 presents how the bullish and bearish periods are identified adopting Dow Theory principles.

Table 3.1: Identification of Bull/Bear Trend According to Dow Theory

Intermediate Up/Down	Bull/Bear	Start Date	End Date
Down	Bear	1,Jun-08	19,Aug-08
Up	Bear	19,Aug-08	5,Oct-08
Down	Bear	5,Oct-08	27,Nov-08
Up	Bear	27,Nov-08	4,Jan-09
Down	Bear	4,Jan-09	9,Apr-09
Up	Bull	9-Sep-2009	17-Feb-2010
Down	Bull	17-Feb-2010	10-May-2010
Up	Bull	10-May-2010	5-Dec-2010
Down	Bear	5-Dec-2010	25-May-2011
Up	Bear	25-May-2011	24-Jul-2011
Down	Bear	24-Jul-2011	6-Feb-2012
Up	Bear	6-Feb-2012	17-Apr-2012
Down	Bear	17-Apr-2012	10-Jul-2012
Up	Bear	10-Jul-2012	23-Sep-2012
Down	Bear	23-Sep-2012	10-Dec-2012
Up	Bear	10-Dec-2012	14-Feb-2013
Down	Bear	14-Feb-2013	29-Apr-2013
Up	Bull	30-Apr-2013	10-Jul-2013
Down	Bull	10-Jul-2013	21-Oct-2013
Up	Bull	21-Oct-2013	6-Feb-2014
Down	Bull	6-Feb-2014	22-Jun-2014
Up	Bull	22-Jun-2014	12-Oct-2014
Down	Bear	12-Oct-2014	4-May-2015
Up	Bear	4-May-2015	5-Aug-2015
Down	Bear	5-Aug-2015	2-May-2016
Up	Bull	2-May-2016	24-Jan-2017
Up	Bull	24-Jan-2017	19-May-2017
Up	Bull	19-May-2017	26-Nov-2017
Down	Bear	26-Nov-2017	18-Mar-2020
Up	Bull	18-Mar 2020	28-July- 2021
Down	Bear	28-July-2021	9-Nov-2021
Up	Bull	09-Nov-2021	30-Dec-2021

Chapter Four- Disposition Effect: An Analysis Across Different Equity Market Conditions

4.1 Introduction

Classical finance was built on the assumptions that economic agents investing in the equity market are perfectly rational, have perfect self-control, and make decisions based on utilitarian theory in a perfect market under the framework of risky environment. This kind of decision-making has been regarded as the theoretical model of investment behavior. The rational behavior of economic agents has been strongly challenged by the emergence of new field of study known as behavioral finance since late 1980s. Over the last three decades of research work in Behavioral finance, it was evidenced that real investment behavior of economic agents influenced by their psychological and emotional traits completely incompatible with what rational expectation theory dictates. An alternative approach to the rational theory applied by investors in their decision-making process is prospect theory of Kahneman & Tversky (1979). This theory is treated as foundation of behavioral finance; a theory that describes the thinking process of investors under risk.

Behavioral finance proposes that investors rationality is bounded; a concept proclaimed by Herbert Simon (1982) indicates that there are always limits to the human learning process, given set of information available and time constraints. Investors are tempted by their own biases and make cognitive errors which may lead to wrong decisions. The striking insights of behavioral finance recognize the ubiquitous, subconscious cognitive biases that occur in human decision-making process and reveal a completely new perspective to study what drives behind the investors' unusual unwanted behaviors.

One of the most powerful empirical findings documented in behavioral finance literature is the disposition effect; a behavioral tendency on the part of the investors in equity market to actualize the stocks more readily which value are in the domain of gains than the stocks which value are in the domain of losses (Shefrin & Statman, 1985; Odean, 1998; Grinblantt & Kelohaiju, 2001; Feng & Seasholes, 2005; Frazzini, 2006; Jin & Scherbina, 2011). The Shefrin and Statman (1985) study first documented the phenomenon of disposition effect bias in equity market perspective proven to be the most substantial findings in behavioral finance.

But the pioneer work on the disposition effect has been conducted by Odean (1998) to empirically test whether investors are more reluctant to realize the losing investment than the gaining one. One possible explanation in favor of disposition effect why investors tend to behave like this is loss aversion phenomenon. It is one of the key elements in prospect theory, which is the center point of behavioral finance. The basic about the loss aversion describes that the ache or annoyance of losses coming from investment is more than twice as they feel the pleasure of making gain from it. Now, let me guess why investors are exposed to the bias of disposition effect? The investors' perception is that selling the winning position in stocks proves that they did the right decision on their trading. At the same time, selling the position at loss would grope investors to admit that they were worthless in dealing the trade. They simply want to avoid regret and pursue pleasure.

The behavioral bias of disposition effect might have some negative consequences on both investors' psychology and investment values. Imagine the situation that losing stocks that investors hold continue to decline and winning stocks that have already sold still kept its momentum up. They might pursue another bad decision by selling the losing stocks and buying back the outperforming stock. At the end, when outperforming stocks start to decline because they have already reached above its fundamental value, frustration will work among the investors, and they would become more panic. Finally, they should cut losses of their investment and blame the market for incurring the loss.

4.1.1 Scholarly Definition of Dispoition Effects

Shefrin & Statman (1985) first empirically investigated the concept of disposition effects in the context of financial market. They define "the reference point effect explains the disposition to sell winning stocks too early and ride losing stocks too long".

"The disposition effect describes a desire for investors to realize gains by selling stocks that have appreciated, but to delay the realization of losses" (Statman et al., 2006).

Bashal (2014) defines "disposition effects as the propensity for investors to realize gains sooner than losses through selling profit making investments more readily than loss making investments".

Gong & Wright (2013) describes the disposition effect as the tendency of investors to realize stocks which have made gains more readily than those which have experienced losses.

The study of Goo et al. (2010) refer to the disposition effect the tendency to sell previously purchased stocks that have appreciated in value and the reluctance to sell those that are trading below their purchase price.

According to Kong, Bai, & Wang, (2015), the disposition effect refers to the tendency of individuals to profit their gaining transactions (winners) too early and the reluctance to realize their losing transactions (losers).

"The disposition effect is the investors' reluctance to crystallize losses and relative eagerness to realize gains, is pervasive across investor classes" (Brown, Chappel, Rosa, & Walter, T.,2006).

van Dooren & Galema (2018) study states "The disposition effect is the tendency to sell appreciated stocks (winners) too early and hold depreciated stocks (losers) too long".

The disposition effect is a bias where investors are predisposed to hold stocks trading at a loss and to sell stocks trading at a gain (Richards, Fenton-O'Creevy, Rutterford, & Kodwani, 2017).

4.2 Research Problem

In financial theory, the decision-making in equity market has been centered through the Efficient Market Hypothesis (EMH). The hypothesis advocates that capital market is efficient at least in weak-form, market participants are rational, have symmetric information, and therefore, any form of anomalies observed in the market will be corrected to restore the equilibrium in the long-run. A vast number of empirical studies over the last three decades report a new approach of research highlighted under the platform of behavioral finance that argue that capital market is not always efficient, and behaviors of all market players are not rational (Akert et al., 2003; Daniel et al., 2002; De Bondt, 1998; Odean, 1998). There are observed systematic erroneous actions taken by market participants which deviate from rational utility maximizing characteristics and are naturally driven by cognitive psychology and emotional motivations. This unusual observed phenomenon is described as behavioral biases. Among the various forms of behavioral biases, disposition effect is the mostly examined bias exists in equity market.

The theory of modern finance presumes that being a rational investor they would hold the winning position in financial instruments and realize the losing position more quickly. This is the case of normative investment principle. There are plenty of empirical findings that prove that investors have the propensity to dispose the stocks that have appreciated in value and prolong the holding period of shares that have depreciated in value (Odean, 1998; Statman et al., 2006; Shapira & Venezia, 2001; Barber & Odean, 1999).

Despite the wide range of empirical studies done on disposition effect bias in different equity markets globally, investigating this behavioral bias phenomenon is still very appealing and thought-provoking issue among the academic researchers particularly in frontier markets like Bangladesh.

4.2.1 Research Question

The extensive evidence regarding the presence of disposition effect bias has been a common phenomenon evolved from existing literature in behavioral finance. The characteristics of this unusual investment behavior on the part of investors irrespective of developed, and emerging equity markets are not warranted on a rational utility theory of classical finance. This kind of investors' behavior opens the avenues for academic researchers to pursue the scope of behavioral finance to determine the psychological and emotional aspects behind this irrational decision.

The research on the disposition effect in global equity market has been extensively investigated by Odean's (1998) framework (Odean 1998; Shapira & Venezia 2001; Dhar & Zhu 2002; Barber et al. 2007; Barberis & Xiong 2012; Barreto et al. 2023). Hermann et al. (2019) applied an alternative model to analyze the disposition effect focusing on the previous day equity prices as reference point. The thesis replaces the previous day's equity prices by the changes in market index to understand how it influences aggregate market trading volume. This alternative disposition effect methodology was not used in any emerging and frontier equity markets to uncover how investors' behaviors vary under different market conditions. The study of Bernard et al. (2018) only examined the disposition effect in boom-and-bust conditions, but not across different equity market conditions. Bangladesh equity market is one of the volatile and less correlated markets in the South Asian region characterized by an insufficient level of regulations, manipulation by stalwart investors, unstructured trading behaviors by investors, and assorted market irregularities.

By addressing this gap, the essay develops the following research question: How does the disposition effect persist in the Bangladesh equity market across different market conditions?

4.3 Theoretical Framework

The propensity of equity market investors to hold the stocks having losses for a long period of time and to dispose of the stocks having gains more frequently has been a common puzzle in behavioral finance literature. There is still no distinctive theory developed explaining why economic agents exhibit this kind of unusual behavior. There are two dividing thoughts developed regarding the possible explanations why investors behave like this. One group of authors reports that there is rational explanation in identifying why disposition effect exists and other group reveal that motivation is solely behavioral. In below part, these theoretical developments are described.

4.3.1 Shefrin and Statman Behavioral Motivation

Shefrin & Statman (1985) were the first to register the existence of disposition effect in the equity market. They developed the framework of four component cognitive theories to describe how the influence of psychology defines the presence of disposition effect.

4.3.1.1 Prospect Theory of Kahneman and Tversky

One of the primary explanations in favor of the disposition effcet is based on the assumption of prospect theory preferences. It is a psychological theory that explicates how people make decisions when confronted with alternatives that invlove risk and uncertainty. Propspect theory is perceived as an alternative approach to the expected utility theory, which describes a rational choice for evaluating economic decisions of investors under conditions of uncertainty.

History of Prospect Theory

The prospect theory sometimes called the loss-aversion theory, was originally introduced by two famous psychologist Daniel Kahneman and Amos Tversky to explain how people make choices under conditions of uncertainty. This theory was incorporated in a paper entiled “Prospect Theory: An Analysis of Decision under Risk” published in the Journal of Econometrica in 1979. This theory has been applied in numerous discipline particularly to analyze the various political decision-making aspects in international relations.

Description of Prospect Theory

Prospect theory specifies that when investors are given equal probability and equal outcome, they would always prefer retaining the current investment value rather than waiting to increase their current value. That means they would feel comfort to ignore a loss than to take a risk for an equivalent gain. According to this theory, investment behavior of investor is judged on the basis of the S-shaped evaluation function. This theory is built on the proposition that investor utility does not depend on the absolute value of the investment rather utility is a function of potential gains and losses in comparison to a benchmark variable. The benchmark for assessing the gains and losses is commonly known as reference point. The most common reference point used in measuring disposition effect is the buying price. When the price of an individual security exceeds the purchase price (domain of gains), investor is said to be in the concave part of his valuation function and is treated as risk averse. Whereas, if the price an individual security drops below the purchase price (domain of losses), investor is said to be in the concave segment of the valuation function and is identified as risk seeker. This reasoning has also been supported by other scholars to justify the presence of disposition behavior by investors (Odean, 1998; Weber & Camerer, 1998). It is believed that when investors become risk averse in gain domain and risk seekers over losses, they have the preferences to hold paper losses and realize the paper gains.

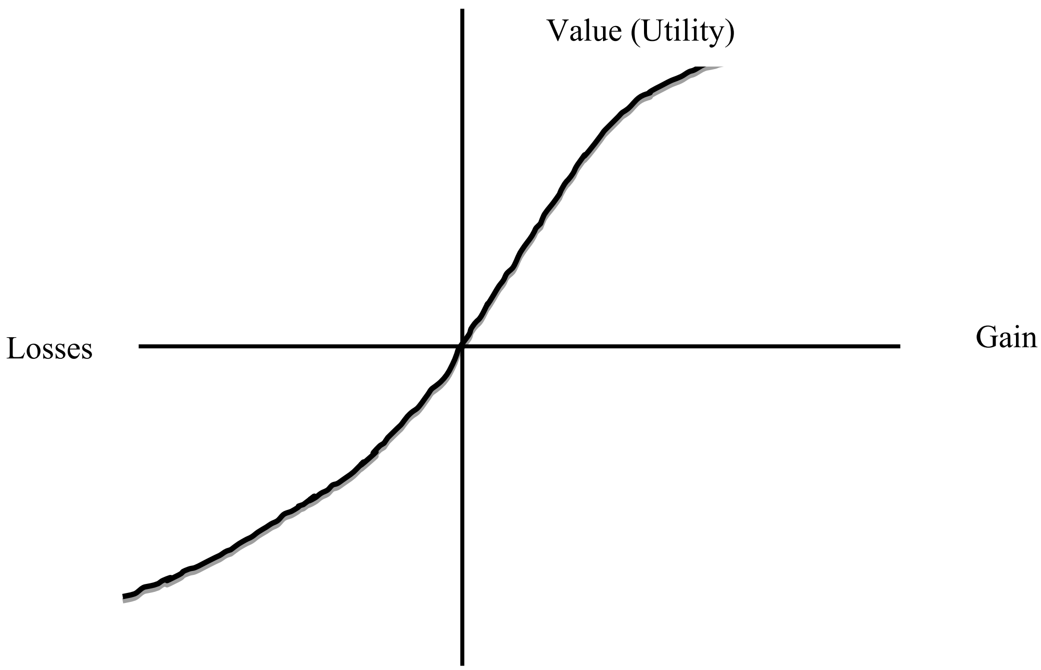


Figure 4.1: Prospect Theory

Their choices rest upon framing of preferences around them around reference point. Prospect theory underscores that investors will have the preference to assess the potential gains and losses of investment with respect to reference point (usually the purchase price) rather than its total value determined using the utility theory. Investors will have different kinds of feelings/satisfaction in potential gains (losses). The essence of prospect theory is summarized through S shape value function. The value function describes that investors display their attitudes of risk aversion when experiences gains (in economic sense refers to concave in the gain region) but demonstrate risk seeking attitudes when experiences losses (known as convex for losses). Attitudes of risk aversion motivate the investors to realize the winning stocks more quickly in order to avoid larger losses. An attitude of risk seeking lures the investors to have a greater aptitude for large losses hoping that finally prices will recover. Thus, this kind of attitude stimulates us to observe the disposition effect (Shefrin & Statman, 1985; Weber & Camerer, 1998; Odean, 1998; Grinblatt & Han, 2005).

4.3.1.2 Mental Accounting

Shefrin & Statman (1985) points out mental accounting as behavioral explanation for the existence of disposition effects behavior. Mental accounting is a behavioral phenomenon of human cognitive processes that highlights the importance of money and how people place different values on the money based on the various subjective criteria. Theory of mental accounting contends that humans categorize the funds differently irrespective of its sources and intended use and tend to make irrational spending and financially detrimental investment decisions. Thaler defined mental accounting as "the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities".

Mental accounting is the tendency of the people to seperate the money into different accounts(purpose)depending on the multiple subjective criteria. We can define this concept with a simple example. People, in genral, have the intention to save money for the vacation purpose while they have the loan obilgations. Here, money saved for travel and money to pay off the loan are treated separately. The question is why people have like this when dealing with money? The answer is cognitive thaught process of humans. That's why mental accounting is regarded as behavioral bias that can affect human behavior. According to the definition of mental accounting, savings should sensibly used to pay off the loans. Becuase it makes sense more to satisfy the loan obligation from all available funds rather than savings for a vacation.

History of Mental Accounting

The notion of mental accounting, a topic in behavioral economics, was introduced by a Nobel Prize winning economics Richard Thaler, a Professor at Booth School of Business, University of Chicago. He published the concept in a paper titled "Mental accounting Matters" in the Journal of Behavioral Decision Making in 1979. In mental accunting theory, Thaler emphased the role of money fungibility that people fail to treat. It defines that money is perfectly fungible (mutually exchnageable) and people should equally manage all money regardless of source or use. Thaler observed that people do not bother about fungibility principle when dealing with money coming from nonregular sources like bonuses, gifts, tax refunds, lottery or any other unplanned sources. People perceive the money coming from any of these sources is not their regular income and they spend the money in a extravagant way. Therefore, Thaler advised that people should value all money the same and spend all money in the same planned way they spend for the regular income.

We can demonstrate the concept of mental accounting theory in respect of finance discipline. Investors in the financial market can behave irrationally and allocate different values to investments categorized in terms of asset class or risk class which may have negative consequences on investment returns. Suppose an investor holds two separate portfolio. One is safe portfolio and other is risky portfolio (speculative motivation). This investor has the preference to value both portfolios separately simply to distinguish the return of one from the return of other investment. But the combined returns to be generated from both portfolios do not make any difference to the investor. The idea of mental accounting is that investors formulates different choices into different accounts and apply the decision rule for each account without accomodating any possible interactions.

The application of mental accounting to equity investment can be structured as follows. Whenever an individual security is purchased, investors maintan a separate mental account for each stock. According to Thaler (1985), investors apply the prospect theory to each mental account. In the first step, they tend to assess the potential gains or losses (paper gains or paper losses) relative to a refernce point for each account. And in the second step, they evalute the investment by maximizing the utility based on S-shaped value function. As we know that S-shaped value function states that investors are risk averse in the domain of gains and risk seeker in the loss domain. Thaler (1985) mentioned that it is more painful for investors to realize any loss than a paper loss. Therefore, investors treat themselves as disgraceful to close any mental account having a loss.

4.3.1.3 The Regret Theory

The third Behavioral explanation in Shefrin & Statman's (1985) framework to support the argument in favor of disposition effect bias in the equity market is regret aversion. The quintessence of this theory is that investors will have the proclivity to liquidate the gaining stocks as early as possible but have the desire to delay the losing stocks to simply avoid the regret.

History of Regret Theory

Regret theory is a known psychological theory proposing that people have the tendency to regret when they find out that their decisions are perceived to be wrong. Regret theory was developed by British economists Graham Loomes and Robert Sugden in the paper titled "Regret theory: An alternative theory of rational choice under uncertainty" published in The Economic Journal in 1982.

The rationale behind the prospect theory based behaviors is the loss aversion. Prospect theory describes the investors behavior on the loss aversion argument that expected utility is measured by the joy and ache they enjoy about the outcome of an investment decision. This theoy does not pay any attention to the emotions emerged from the outcome itself. Whereas the regret theory incorporates emotional aspects into decision process and states that people have the desire to compare the outcome of an investment decision with other alternative outcomes and develop feelings about whether the outcome is better or worse (Zeelenberg et al., 2005).

The aspect of regret is viewed in a financial decision as a negative feelings which forces the investors to make sub-optimal biased decisions (Michenaud & Solnik, 2008). It was argued that investors not only focus on the potential gains or losses on the investments but also consider the regret they feel about the possibles outcomes on those investments. Suppose when an investor gets a return from an investment which becomes lower relative to other alternative investment they feel regret that a bad decison was made.

Regret (feelings associated with loss) and pride (relevant to gain) act as a behavioral motivation for the disposition effects phenomenon proposed by Shefrin & Statman (1985). The hypothesis is that if an investor incurs a loss due to the decline in the share price, he/she would feel regret on the motivation that a bad investment was made. Under this situation, investor tends to hold the stock with the believe that share price will revive back. On the other hand, if the share price increases and investor gains, he would feel pride acknowleding that investment decision was good. Thus, investor will have a strong preference to realize the gain. This is how the feelings of pride and regret may motivate the investors realizing the winning stock ahead of losses and exhibit the disposition effects.

Another aspect Shefrin & Statman (1985) observed in regret theory that the extent of feelings of regret about an bad investment decision are not sensed equally in case of realized and unrealized losses. This means regret theory defines that the emotional feeling of regret is perceived to be lower for realized losses than for any unrealized action. The motivation is that by holding the losing stock with the expectation that the share price will return back to its purchase price, an investor tend to reduce his feelings of regret about the decision.

4.3.1.4 Self-Control

Shefrin & Statman's (1985) work presented a fourth behavioral explanation why investors in the equity market possess the disposition effect bias is the lack of self-control. They introduced a model that identified two facets of human brains. The first one is the "rational planer" part of the brain and the second one is the "myopic doer" side of the brain. The planner part sensitively comprehends the aspects of realizing gains more readily than the losses noticed in the disposition effect. But the doer part has the myopic tendency to recourse emotional regret aversion lesson and convinced to do their investments actions. The implication is that the first part of the brain has been incapable of disregarding the second part, thus showing the reflection poor class of self-control which leads to the disposition effect. It is also explained by Fischbacher et al. (2017).

4.3.2 Odean's Framework of Rational Motivation

In addition to the behavioral motivation described above, there are some rational explanations for the presence of disposition effect in the equity market.

4.3.2.1 Mean Reversion

Barber & Odean (1999) argue that the expectation of short-term Mean-reversion could be a strong rational reason for investors exhibiting the disposition effect phenomenon. It is presumed that investors selling the winning position quickly with the prediction that it will revert to its intrinsic value (fundamental) in near future and defer to sell the losing position with anticipation that its value will increase up to the fair value. Weber & Camerer (1998) made the contrary argument that short-term mean reversion is not rational and unwarranted because it goes against the rational expectation theory assumption of the market efficiency hypothesis that the equity market will always revert to the mean fundamental value.

4.3.2.2. Portfolio Rebalancing

The second rational justification for the existence of disposition effect behavior on the part of investors is the concept of portfolio rebalancing. Investors tend to deliberately maintain a target level of allocation of each stock (to maintain the weight of each stock constant) through periodic buying and selling in a portfolio. Portfolio rebalancing enhances the capacity of investors to ensure the portfolio exposure to undesirable risks. Investors sell the stocks with positive gains to substitute by other stocks to have their portfolio well-diversified. On the other hand, they avoid selling the losing stocks to preclude the dilution of the portfolio. Thus, the puzzling of disposition effect bias could be the outcome of investors' way of keeping their portfolio diversified (Odean 1998).

4.3.2.3 Transaction Cost

Another rational but less contributory reason for the disposition effect is transaction cost incurred by investors developed by Odean (1998). It is perceived that transaction costs for investors in realizing the losing position of stocks are relatively higher than selling the gaining position in stocks. This aspect of trading behavior might assist investors to prevent selling the stocks which value decline and help induce them to sell the stocks which value increased. This transaction cost has also been supported by the study of Brown et al. (2006).

4.3.3 Other Possible Behavioral Explanations

4.3.3.1 Overconfidence

Investors in the equity market are overconfident that they possess superior information about the market. But they lack the precision of information while making their investment decisions. The idea behind the overconfidence bias is that when prices tend to increase investors presume that they reach the maximum value, and they will realize the gain. Whereas, when prices represent a downward phase, they feel the prices can’t continue to decline further and they will come back towards a positive trend. This kind of overwhelming behavior can lead to a disposition effect. It is supported by Ben-David & Doukas (2006), and Liu & Chen (2008).

4.3.3.2 Cognitive Dissonance

Cognitive dissonance is the kind of unpleasant feelings of investors’ characteristics observed in their decision-making process because they hold the two incongruous beliefs at the same time. This irrational decision-making may lead to disposition effect as investors make efforts to reconcile their conflicting beliefs with the exercise of buying/selling decisions impulsively.

Figure 4.2 portrays the framework about how investors in equity market demonstrate the behavioral bias of disposition effect in their investment decisions process. There are two thoughts of explanations addressed from existing literature.

First thought of explanation is identified as rational behavior justified by the modern finance theory. The second thought of explanation is the behavioral phenomenon adequately supported by cognitive and personality psychology. Each form of explanation has been depicted in above section of the study. The lower part of the diagram presents how social psychology comes into picture to indirectly affect the disposition effect through the cognitive characteristics of investors.

Although there is lack of empirical evidence in favor of social of psychology to explain the disposition effect, it is developed from the theory that investors' behaviors are strongly affected by social influence. Social psychology emphasizes how the perception, attitudes, feelings, and actions of investors are affected by social influence (behaviors by others and groups). There are three elementary dimensions of social influence. Conformity is the kind of behavior of investors brought about by a desire to follow the beliefs or standards of others. Compliance is the behavioral phenomenon that results from direct social pressure. Obedience refers to the change in behavioral attitudes of investors in response to the command of others.

4.3.4 Fundamental Behavioral Mechanisms behind Disposition Effect

The disposition effect is explicable by two mechanisms of psychology which are interconnected such as loss aversion and mental accounting. Prospect Theory (Kahneman and Tversky, 1979) states that investors compare the results with a point of reference, which in most cases is the price of acquisition, and are more sensitive to a loss than a gain. The perceived disutility of a loss is much higher than the utility of a comparable gain, which means that investors will avoid the realization of losses where it is rational to take a loss. This tendency of behavior introduces inertia in positions of losses and price underreaction that strengthens when the markets are down.

Mental accounting also increases this, with the effect that investors separate each investing decision into a discrete psychological account. The profits in one account are not easily compensated for by the losses in another which makes the investors view the realized losses as personal failure instead of an aggregate portfolio strategy. Consequently, they procrastinate in selling losing stocks in order to escape regret as well as to preserve an illusion of control over unrealized losses. A combination of these mechanisms justifies the stronger disposition effect of the bearish and crisis market conditions in the Bangladesh equity market where information uncertainty and emotional trading are higher among the retail investors.

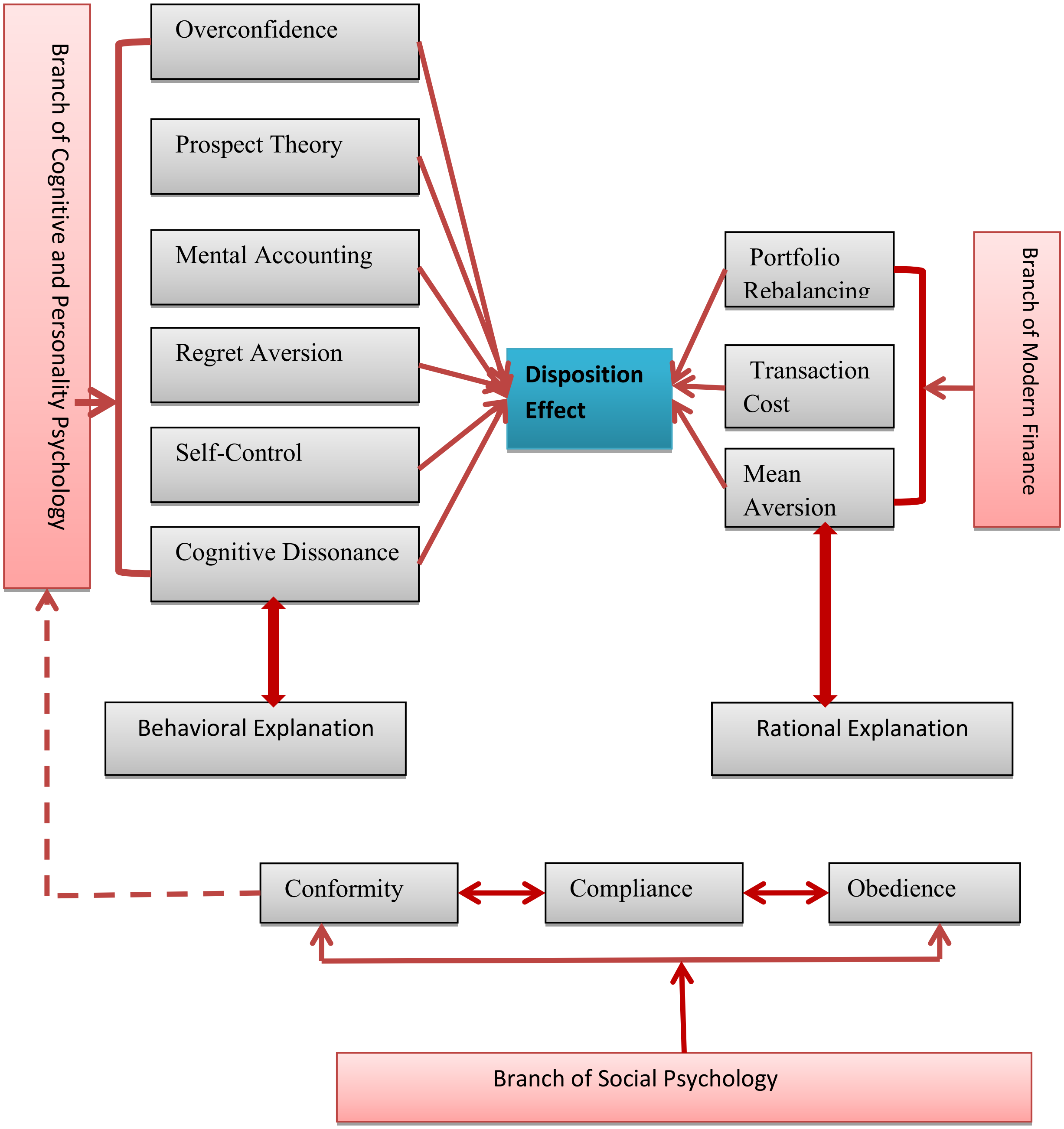


Figure 4.2: Theoretical Approach to Disposition Effect

4.4 Literature Review

Behavioral finance studies over the last three decades established that decision-making process of investors participating in equity markets are seriously influenced by their psychological and emotional characteristics which neoclassical finance theory failed to successfully vindicate. Unnumbered empirical studies are reported on the issue of disposition effect biases incurred by investors from equity market. The section below makes the effort to summarize the updated literature on the authoritative disposition effect bias from existing literature.

4.4.1 Investor Heterogeneity and Behavioral Implications

Even though data applied in this analysis is aggregated on the market level, the behavioral explanation provides a strong indication of heterogeneity between the classes of investors. Retail investors dominate the Bangladesh equity market, are mostly more sensitive to the short-term fluctuations in the market, are more prone to heuristic decision making and less likely to use professional advisory services. The disposition effect that is present therefore, particularly in bearish and crisis times, must be motivated, in large part, by individual investors who exhibit greater emotional reactions to losses and gains.

On the contrary, institutional investors are smaller, but they are more likely to adopt trading and portfolio rebalancing strategies that curtail emotional influences. Thus, the variations in investor sophistication, availability of information, and investment time represent the strength of asymmetry in the disposition effect behavior under different market conditions. It is important to identify these behavioral differences when determining the impact of market composition on aggregate trading patterns in frontier markets.

4.4.2 Empirical Evidence on Disposition Effect

Shefrin & Statman (1985) were the first contributed to literature to document the presence of disposition effect in equity market. They analyzed two aspects of the disposition effect. First, they mainly developed the theoretical framework to explain why investors display disposition effect. These are prospect theory, mental accounting, regret aversion, self-control, and tax-consideration. Second, they evidenced that only tax considerations fail to explain the loss and gain realization patterns, rather these patterns are more observed with combined effects of tax considerations along with other theories. They also conclude that the tendency of investors to concentrate on loss realizations in December is not found supportive with rational behavior model but is more aligned with their theories.

Odean (1998) tested the disposition effect by analyzing 10,000 trading accounts of individual investors at a nationwide large discount brokerage house for the US equity market over the period from January 1987 to December 1993. Based on the proportion of gains realized (PGR) over the proportion of losses realized (PLR), he found that investors showed a strong preference for realizing profitable stocks than the losing stocks except for December (because they have the tendency to engage in tax-motivated trading during this month). The behavior of investors does not seem to be determined by their willingness for rebalancing the portfolio or refraining from selling to higher trading costs in low priced securities. The disposition effect was investigated in New Zealand equity market by Taylor (2000). They used 125 trading accounts of retail brokerage houses over the period of 1988-1999. He performed the disposition effect with respect to two different set of reference points. The basis of first reference point was average purchase price of the instruments, whereas other reference point used was the relative strength measure. He found that investors do exhibit a minor disposition effect when first reference point was used. But he did not find any behavior of disposition effect in New Zealand equity market when second sort of reference point was adopted. Interestingly, the disposition effect evaporated when data set is enlarged to include additional sales.

One of the behavioral puzzles known as disposition effect has been studied in US equity market by Ranguelove (2001) using the data from June, 1991- December, 1996. His study took daily trading records of 7800 clients from a major discount brokerage house. They find that trading stocks at bottom 40 percent of market capitalization distribution display a reverse disposition effect: holding the winning stocks too long and disposing the losing stocks quickly. He assumed that investors are more motivated to realize the gain and delay the losses for the firms with large market capitalization. They also pointed out that it is the beliefs of investors rather than preferences which generate the disposition effect. The findings challenge the mostly developed proposition from literature that disposition effect is the outcome of prospect theory-based investors behavior.

Shapira & Venezia (2001) tested disposition effect considering the trading records of all transactions of large major brokerage house in Israel during the whole period of 1994. They mainly attempted to measure whether the disposition effect prevails for two types of investors: Independent investors, who manage their own portfolios and professionally managed fund managers. Results manifest that both professional and individual investors exhibited the disposition effect, but the effect was more robust for individual investors. They also showed that the average duration of the winners was significantly shorter than the duration of the losers.

Dhar & Zhu (2002) analyzed the disposition effect using the transaction records at a major discount brokerage house from the US equity market. Their study mainly focused on identifying the investors' characteristics (demographic and socio economic) to explain why individual differences in the disposition effect exist. They found that investors' sophistication partly could induce the different level of variations in individual disposition bias among them. Their empirical evidence also indicated that wealthier investors with professional experiences can lower level of disposition effect in the US market.

Brown et al. (2006) examined the disposition effect in the Australian equity market for all investors in both initial public offerings (IPO) and index stocks over the period from 1995 to 2000. They revealed that the disposition effect is pervasive across investor classes in Australian market. They discovered the findings including i) the disposition effect gradually dwindles as investors holding period increases. They become indifferent between gain and loss realization after 200 trading days from the purchase price, ii) the disposition effect was influenced by the house money effect, and iii) the disposition effect was reversed in June, which is the last month of the Australian tax year.

Barber, Lee, Liu, and Odean (2007) analyzed all trading transactions activities that existed in Taiwan stock exchange during the period 1995-1999 to test whether aggregate and individual investors have the tendency to exhibit the disposition effect. They found strong evidence in favor of the disposition effect in Taiwan market, but results indicate that aggregate investors are about as twice to sell the gaining stocks as the losing ones. On the other hand, among all Taiwanese investors, 85 percent are more willing to sell the winning stocks more readily than the losing stocks except the two classes of investors: investors in mutual funds and foreign investors. These two groups constitute for only less than 5 percent of all market trade. The most promising and commonly used explanation for the prevalence of the disposition effect in the equity market is the prospect theory. Barberis & Xiong (2009) analyzed this puzzling trading behavior of investors with prospect theory preferences. They argued that the association between the disposition effect and prospect theory was not obvious as theoretically thought. In some cases, prospect theory can predict the disposition effect, but in other cases, we observe the reverse effect. Their study focused on this aspect and found that no strong connection was developed between existence of the disposition effect and prospect theory preferences.

How preferences and beliefs inspired the trading behavior of individual investors from a major US brokerage house was examined by Ben-David & Hirshleifer (2012). They documented that realization preferences of investors do not affect their trading behaviors. Weak evidence in favor of upward jump is observed to make the sales at zero profits. They found that disposition effect was not the outcome of inventors' preferences for selling the stocks on the basis of gains but not for losses. These findings can be explained by trading behaviors based on belief reversions. A different equilibrium model has been prescribed by (Li & Yang 2013) to examine the application of prospect theory (defined by S shaped value function) for individual trading behaviors in security prices. They prove that under the framework of Tversky & Kahneman (1979) parameter, prospect theory has the capacity to predict the disposition effect producing a momentum phenomenon in cross sectional returns. Therefore, stimulating the significant pattern of trading behavior observed in upswing markets than in declining markets.

Frino, Lepone & Wright (2015) scrutinized whether disposition effect prevails in the Australian equity market using 46248 transaction accounts from a retail brokerage house from October 1, 2010 to August 31, 2012. By using Odean's (1998) model, they examined the investors' characteristics on their trading behaviors and how they would expose to disposition effect bias. It was evident that women, older investors and investors having Chinese background displayed significant level of disposition effect bias in the Australian equity market. Their study also observed that trading frequency, round size heuristics, and portfolio diversification capacity of investors could drive the disposition effect.

Dai et al. (2019) proves that all the disposition effect patterns observed in the existing literature can be executed following the optimal trading strategies by portfolio rebalancing models whether they consider with or without tax phenomenon. They also find that the probability of selling pressure increases with respect to the magnitude of losses that is identified to be contradictory for the prospect theory and the theory explanations.

The two competing explanations for the disposition effect developed from existing literature are the prospect theory and the regret theory. Sudirman et al. (2017) critically studied both the theories along with a new explanation for this phenomenon called regulatory-focus theory. The kea idea behind this theory is that investors can be categorized into the prevention group and the prevention group. They find that regulatory-focus theory points out a specific argument that the disposition effect is more pronounced for the prevention group rather than the promotion group.

Hermann et al. (2019) made an experimental analysis on the disposition effect for the case of investors who trade on behalf of others. They developed that trading done in favor of other investors significantly influences the disposition effect when investors are inexperienced. This happens because investors are motivated by self-control and feel more comfortable when they are acting on behalf of others. They did not have any disposition effect when subjects become more experienced. This brought important insights for managerial behavior in delegated investment decisions highlighting that prosociality may prevent trading efficiency in case of inexperienced investors.

Dierick et al. (2019) examined the relationship between the disposition effect and financial attention using more than 65000 clients from large brokerage house in Belgian equity market over the period 2014-2016. They found that investors having more attention have stronger tendency to display disposition effect than the less attentive investors. The findings are strongly aligned with the behavioral theory of cognitive dissonance and saliency effects.

Zahera & Bansal (2019) systematically reviewed the disposition effect over a period of 35 years research articles in the area of behavioral finance. They demonstrated that the disposition effect was measured by applying the different methodologies like the ratio of PGR-PLR, ANOVA, t-statistics, correlation and regression analyses. The analysis showed that individuals are more likely to exhibit the disposition effect, but its magnitude vary with the factors include, gender, experience, education, age, and investor sophistications. In contrast, institutional investors consistently display weaker evidence of the disposition effect. The existence of the disposition effect brought important implications for the market participants and policymakers to understand the level of equity market efficiency. This literature also stated that emerging equity markets remain underexplored, indicating a huge research gap for further study on this behavioral bias.

Bharandev & Rao (2020) conducted an empirical analysis on NSE500 index stocks in Indian equity market by calculating winning and losing stocks using 52-week high and low prices as reference points to measure the disposition effect. Results indicate that an abnormal trading volume of a stock has a positive relationship with the percentage of winning days, even after controlling for liquidity and volatility aspects of the market. The percentage of lost days did not display any disposition effect. The study also confirmed the limited research on the disposition effect in an emerging equity market like India.

Hincapié-Salazar & Agudelo (2020) was the first to investigate the disposition effect by comparing both bonds and stocks trading using the individual investors proprietary transaction data from an emerging equity market of Colombia. Applying the Odean's (1998) methodology of PGR-PLR, they found that the disposition effect was present in both bonds and stocks, but it was much lower for the treasury bonds. Further, they confirmed that the institutional as well as foreign investors do not display any disposition effect in this market.

Sadhwani & Bhayo (2021) investigated the relationship between the disposition effect and momentum in the US equity market using daily data of closing stock prices, trading volumes, and market capitalization all common securities over the period from January 1963 to December 2020. To examine this relationship, they utilized Fama-Macbeth regression. The results evidenced that the disposition effect drives momentum, but momentum cannot affect the disposition effect. It was also found that along with the disposition effect, size can influence momentum.

In another study by Bharandev & Rao (2021) examined the disposition effect and anchoring bias in Indian stock market with the help of the market-level data. The disposition effect was used as proxy variable by the abnormal trading volume, which results in finding that, with the exception of highly liquid Nifty50 stocks, abnormal trading volume is more common on winning days than losing days. This underscores the importance of revised reference points and historical price anchors to investor behavior, which provides information that becomes useful in trading and portfolio choices.

Liu et al. (2023) conducted an examination of the disposition effect and the unique characteristics of momentum/contrarian behaviors in the Taiwan Stock Exchange. Among the conclusions is the fact that individual investors have a stronger disposition effect than other investors. Furthermore, they discovered that whilst individual investors tend to pursue more contrarian strategies; investment trusts, as well as foreign investors, are found to be momentum trader.

Ahn (2024) discloses that there is a positive correlation between the indicator of disposition effect in the gain domain and the one proposed by Odean. Conversely, there is no correlation between the measure of Odean (1998) and the disposition effect measure in loss domain. The research evidenced an asymmetric behavior in the gain and loss domains of investment decision-making that might lead to suboptimal results.

Zhang, Ma, & Zhang (2022) Examined the relationship between effect and disposition effect, and social comparisons influence with a laboratory experimental approach. They experiment with two types of interventions: a) changing effect of sensitivity of financial disclosures and b) the role of financial models. Results evident that both interventions can reduce the disposition effect by encouraging loss realization and discouraging the profit taking preferences of investors. They mentioned that highly sensitive financial disclosures lower the disposition effect by almost 41 percent, and introduction of financial role models reduces the disposition effect by roughly 50 percent relative to the other control controls.

Quispe-Torreblanca et al. (2025) used online brokerage data from Barclays Stock broking in the United Kingdom covering the period from April 2012 to March 2016 to examine how investors login in trading behavior can influence the disposition effect. They considered a new reference point by identifying investor portfolio position when he/she logged in. They confirmed strong presence of the disposition effect measured based on the return since last login versus return based on the purchased price.

4.3.2 Hypotheses Development

The study by Zhang et al. (2022) from the Chinese equity market documented the evidence that retail investors will exhibit stronger disposition effects when they approach the market for the first-time during periods of lower market return, higher market volatility, or worse investor sentiment. As both bullish and crisis markets often lead to high market volatility, investors tend to display disposition effects that are high in volatile markets. As a consequence, it is expected that investor trading behavior will display disposition effects that are high in both bullish and crisis market conditions. Bernard et al. (2018) provided evidence from developed equity market in Germany that the disposition effect is countercyclical, recognizing its weaker presence in boom markets but higher in crash markets. This happens due to the tendency of investors to shift attitudes and risk aversion during these market cycles. The discussion of these behavioral patterns from developed and emerging equity markets has led to the formulation of the following hypotheses:

Hypothesis One: Investors in the Bangladesh equity market, a frontier market, will exhibit a disposition effect in their trading behavior for the entire period.

Hypothesis Two: Investors' trading behavior will display disposition effects that are high in volatile markets, and therefore, it is also high in bullish and crisis markets on account of their market volatility.

Hypothesis Three: The disposition effect may become more pronounced and stronger in the crisis (crash) market period in relation to the bullish (boom) market period.

4.5 Data and Methodology

4.5.1 Data

The thesis utilizes large data set that spans from January 1, 1993 to December 31, 2020 for measuring the disposition effect in the Bangladeshi equity market. There are two types of data formulated for the study: One is the Dhaka stock exchange broad index, and the other is the trading volume of aggregate market determined by summing up the turnover ratio of all the listed common stock on the Dhaka stock exchange. In the case of the market index, two categories of indices are taken into consideration. DSE General Index was used from January 1, 1993 to June 1, 2013 and the DSEX Index for June 28, 2013- till today. All data is collected from the data source of the Dhaka stock exchange library.

During the study period, the Bangladesh equity market went through two massive crushes. One happened in 1996 when there were paper-based stocks and the second crush occurred in 2011 under the framework of electronic-based stocks. But the overall movement of the equity market continues to exist on a downward trend since 2011. To explore the level of investors' preferences to exhibit the disposition effect concerning various forms of market phenomena, the entire study period is sub-divided into four market segments: The bullish period, the bearish period, the crisis period, and the extended crisis period.

4.5.2 Methodology for Measuring the Disposition Effect

The majority of the empirical studies on disposition effect behavioral bias prevalent in the equity market thoroughly evidenced the Odean (1998) framework, which is the ratio of the proportion of gain realized (PGR) to the proportion of loss realized (PLR). The disposition effect states that throughout the year, trading volume in capital-losing stocks will always be less than trading activity in gain-producing stocks (Ferris et al. 1988).

In the present study, to compute disposition effects–the propensity of investor investors to sell stocks that have increased in price while holding onto those that have decreased–we utilize Weber & Camerer's (1998) measure. Hermann et al. (2019) have also computed the disposition effects (DE) with the measure (alpha) of Weber & Camerer (1998), in addition to the DE measure of Odean (1998). Hermann et al. refer to this metric as the "alpha" metric.**Error! Reference source not found.** Though alpha looks at whether investors made use of the market prices from the previous period as a benchmark, this paper replaces the market price in the previous period with the market index of the previous day.

To calculate the coefficient of the disposition effect, the methodology incorporates the influence of the level of daily trading volume of the aggregate market based on the direction of the rate of return of the preceding day's market index. The model of measuring the disposition effect is as follows:

$$\alpha_{i+1} = \frac{\left[\sum_j^n V_+ - \sum_j^n V_-\right]}{\left[\sum_j^n V_+ + \sum_j^n V_-\right]} \qquad (4.1)$$

where, α_{i+1}= is the disposition effect coefficient of i + 1 week, i = 0,1,2,........................,m

V_+ = is the trading volume of the present day if the market index of the preceding day increased
V_-= is the trading volume of the present day if the market index of the preceding day decreased
$\sum_j^n V_+$= Sum of V_+ from the j day to the n day
$\sum_j^n V_-$= Sum of V_- from the j day to the n day
j = Starting day where, $j = 5i + 1$
n = Ending day where $n = 5(i + 1)$

A positive value of α_{i+1} indicates that the disposition effect prevails in the market; on the contrary, a negative value of α_{i+1} represents that the disposition effect does not prevail. That α value equals to 1, which signifies a stronger form of the disposition effect.

The statistical significance of the coefficient of the disposition effect was tested using both distributional and distribution-free tests (non-parametric).

4.5.2.1 Distributional Test

T test

T test is the basic distributional test used to determine the data for normality that can be described by two parameters (mean and standard deviation). Test statistics for typical t test is:

$$t = \bar{x} - \mu \Big/ S\sqrt{n} \qquad (4.2)$$

This statistic indicates how precisely the sample estimates the population mean.

4.5.2.2 Distribution Free Test

Proportion Test

Proportion test is a non-parametric test employed to measure whether an observed proportion possesses a specific trait and is statistically different from hypothesized value. The test statistics (known as z test) can be developed as follows:

$$Z = \frac{\hat{\pi} - \pi_0}{\sqrt{\pi_0 (1 - \pi_0)}} \qquad (4.3)$$

It approximates to Normal distribution with mean 0 and standard deviation of 1.

Sign Test

Sign test is the median test which is better measurement of central tendency of the data series than average when data becomes non normal. It prescribes the statistical significance of hypothesized median value for a data series indicating whether median value of the data is significantly different from hypothesized value. In case of sign test, we will assume normal approximation to bionomical distribution. The test statistics for Sign test is defined as:

$$Z = \frac{(X + .5) - (\frac{n}{2})}{\frac{\sqrt{n}}{2}} \sim \text{Normal} \quad (0,1) \qquad (4.4)$$

Where $\mu = \frac{n}{2}, \sigma^2 = \frac{n}{4}$

Wilcoxon Ranked Sign Test

Wilcoxon ranked sign test is a rank-based non-parametric location test to assess whether median value of the sample is statistically different from theoretical value.

Suppose given the sample $x_1,.........x_n$ from where $d_i = x_i - M_0$, M_o is the specified value of the median. Let us mention T^+ where, $T^+\ T^+ = \sum_{i=1}^{n} I_{di\geq 0}(d_i)R(|d_i|$, here, , $R(|d_i|$ indicates the rank of $|d_i|$ when $|d_1|,............|d_n|$ are developed in order of magnitude.

The Wilcoxon rank sign test statistics can be identified as:

$$Z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \tag{4.5}$$

Where, $T = \min\ (W^+, W^-)$

And, $E(T) = \frac{n(n+1)}{4}$, $\sigma_T = \sqrt{\frac{n(n+1)(2n+1)}{24}}$

4.5.3 Statistical Reliability and Robustness

Though the disposition effect analysis presented in the thesis is performed, predominantly with the use of distributional and non-parametric statistical tests instead of regression estimation, some steps were made to be able to guarantee robustness and reduce the possible biases during inference. One, the application of several complementary tests, the parametric t-test, proportion (Z) test, and non-parametric Wilcoxon signed-ranked test, permits the constant validation of the disposition coefficient in various distributional assumptions. The similarity of the outcomes of these tests gives substantial reasons to believe that the results are not caused by sample-specific abnormalities or nonconformity to normality.

Second, to ensure that any empirical evidence of trading asymmetry was not due to noises or effects of the microstructure in the equity markets, the analysis has been investigated in different market states, i.e., in bullish, bearish, crisis, long crisis and COVID-19. The prevalence of the bias in these market phases highlights temporal stability of the disposition effect in the Bangladesh equity market.

Third, an adjustment of market index values is the benchmark in the determination of reference prices, thus reducing bias in measurement caused by corporate activities like dividends and bonus shares. This makes gains and losses determination to be based on the actual economic value as opposed to accounting distortions.

These methodological variations confirm the dependability of the findings and ensure that the documented disposition effect is not merely a statistical or structural artifact rather a representation of investors' behavioral tendencies.

4.6 Empirical Results and Findings

Before analyzing the results of the disposition effect, table 4.1 presents the scenarios of movement of Dhaka stock exchange broad index and the aggregate trading volume of market consociated with various market sub-periods. The average rate of market return is identified as 0.055% during the entire study period, whereas it was 0.10% and 0.17%, respectively, for bullish and bearish periods. In the case of trading volume, the mean value remains to be persistent during all sub-period except for the entire period. The aggregate market volume increased during this period by 750%. On the other hand, the movement of median trading volume registered a negative change during each category of segmentation. Although the Bangladesh equity market is treated as an unpredictable emerging market, the changes of its broad index are found to be very nugatory in all breaks down categories of the study periods. A similar finding is observed for the direction of trading volume except for the entire period. The characteristics about the overall movement of the equity market in Bangladesh presented in table 1 deemed to be a curious concern of the study to examine whether investors do demonstrate the disposition effect bias.

Table 4.1 Changes in Market Index and Trading Volume of Dhaka Stock Exchange

	Daily Market Index (% Change)			**Daily Trading Volume (% Change)**		
	Mean	Median	SD	Mean	Median	SD
Entire Period	0.0554197	0.0248772	1.4860272	750.1218	-0.0306751	38287.503
Bullish Period	0.1035407	0.1099969	2.153853	2.079889	-10.945284	20.562422
Bearish Period	0.1701587	-0.1340094	8.319918	3.4872106	-0.2804748	37.194803
Crisis Period	0.0343842	0.2362632	2.7213912	3.4602550	-0.9999159	29.894365
Extended Crisis Period	0.1072979	0.1622650	2.4403133	2.717319	0.3450214	24.73583

Table 4.1 reports the summary results of the disposition coefficients test using the distributional t-test. Results uncover that the coefficient of disposition effect has been found positive and statistically significant for the entire study period. It is also noticed that coefficients of disposition effect persist significantly for the bullish period, crisis period, as well as extended crisis period. It is not found significant for the bearish period. The deduction can be drawn that investors, in general, actively participating in Bangladesh equity markets display the disposition effect bias in their investment decision behaviors. Although the disposition effect is present in the Bangladesh equity market, the magnitude of the disposition coefficient is not much strong.

Table 4.2 Test of Disposition Coefficients Using Distributional Test

	Distributional Test (T-Test)			
	Disposition Coefficient			
	Mean	SD	t -value	P-value
Entire Period	0.057915617	0.535002988	3.98041012	0.000***
Bullish Period	0.173644286	0.52185994	5.32385868	0.000***
Bearish Period	-0.056610056	0.501639958	-1.7771631	0.038
Crisis Period	0.222556018	0.540185856	2.97096684	0.002
Extended Crisis Period	0.147985053	0.519101492	3.22530328	0.000

Note: ***Significant at the 1% Level

Table 4.2 manifests the results of disposition coefficients applying the nonparametric proportion test. The key idea about the proportion test is that it attempts to assess whether the population proportion of positive disposition coefficient is significantly different from a hypothesized mean. Results from the proportion test stipulate that proportion of majority disposition coefficients is positive and statistically significant for all the fragmentation of the study period except the bearish period**.** The rejecting of the null hypothesis magnifies that there is enough evidence that positive disposition coefficients are significantly greater than the negative disposition coefficients suggesting that disposition effect bias present in the Bangladesh equity market.

The outcome is precisely similar to what we observe in the t-test case. Consequently, the distribution-free proportion test also substantiates the presence of behavioral bias of disposition effect among the investors in the Bangladesh equity market.

Table 4.3 Test of Disposition Coefficients Using Nonparametric Proportion Test

Distribution Free Test : Proportion Test			
	Disposition Coefficient		
	Population Proportion	Z Value	P Value
Entire Period	0.54471544	3.2895498	0.000***
Bullish Period	0.65234375	4.87500	0.000***
Bearish Period	0.4596774	-1.270001	0.897
Crisis Period	0.6538460	2.218801	0.013**
Extended Crisis Period	0.6171880	2.65165	0.004***

Note: ***Significant at the 1% Level
** Significant at the 5% Level

The statistical findings of disposition coefficients enforcing the nonparametric methods of both the sign test and Wilcoxon ranked sign test have appeared in Table 4.4. The major advantage of both these two tests over the distributional t-test is that the former measure the location of the distribution in terms of median value rather than mean parameter. Results signify that median values of disposition coefficients are positive for all the market segmentation of the study period except the bearish one. The riveting outcome is developed from the test specifying that disposition coefficients are neither significant for the entire study period nor the all-other periods of market segmentation under sign test. But it is found statistically significant for all the study fragmentation periods under Wilcoxon ranked sign test. The unblemished conclusion can be initiated that the presence of disposition effect exists in the Bangladesh equity market in all format of statistical tests conducted in the study.

Table 4.4 Test of Disposition Coefficients Using Nonparametric Sign and Ranked Signed Test

Distribution Free Test: Wilcoxon Sign and Ranked Sign Test			
	Disposition Coefficient		
		Sign Test	Wilcoxon Ranked Sign Test
	Median	Test Statistics	Test Statistics
Entire Period	0.061924598	-0.10859	-16.0170
Bullish Period	0.218398042	0000001	-6.90507
Bearish Period	-0.061330447	0.063500	-6.87901
Crisis Period	0.188401825	0.138675	-3.07814
Extended Crisis Period	0.161084234	0.088388	-4.87759

Note: ***Significant at the 1% Level
** Significant at the 5% Level

4.6.1 Statistical Properties of the Disposition Effect Coefficient

Table (4.5) (4.6) (4.7) summarize the statistical properties of the disposition effect coefficient presented in Table (4.2) (4.3) and (4.4) for the whole study period as well as for the bullish, bearish, crisis, and extended crisis markets.

Table 4.5 Basic Statistics of Disposition Coefficients for Entire Study Period

Mean	0.058
Median	0.062
Mode	1
Standard Deviation	0.536
Kurtosis	−0.750
Skewness	−0.031
Count	1427

Table 4.6 Basic Statistics of Disposition Coefficients for Bearish and Bullish Period.

Bearish Period		**Bullish Period**	
Mean	−0.011	Mean	0.178
Median	−0.05	Median	0.22
Mode	1	Mode	1
Standard Deviation	0.503	Standard Deviation	0.524
Kurtosis	−0.624	Kurtosis	−0.574
Skewness	0.121	Skewness	−0.284
Count	372	Count	257

Table 4.7 Basic statistics of disposition Coefficients for Crisis and Extended Crisis Period.

Crisis Period		**Extended Crisis Period**	
Mean	0.223	Mean	0.148
Median	0.188	Median	0.161
Mode	1	Mode	1
Standard Deviation	0.545	Standard Deviation	0.521
Kurtosis	−0.865	Kurtosis	−0.668
Skewness	−0.169	Skewness	−0.03
Count	52	Count	128

The coefficient represents the extent to which investors tend to exhibit the disposition effects. Figure 4.2 describes how fluctuations in the value of the disposition coefficient happened across various market segments. The graph would provide insight into the pattern of investors' behavior in the Bangladesh equity market, which can influence their trading and investment strategies.

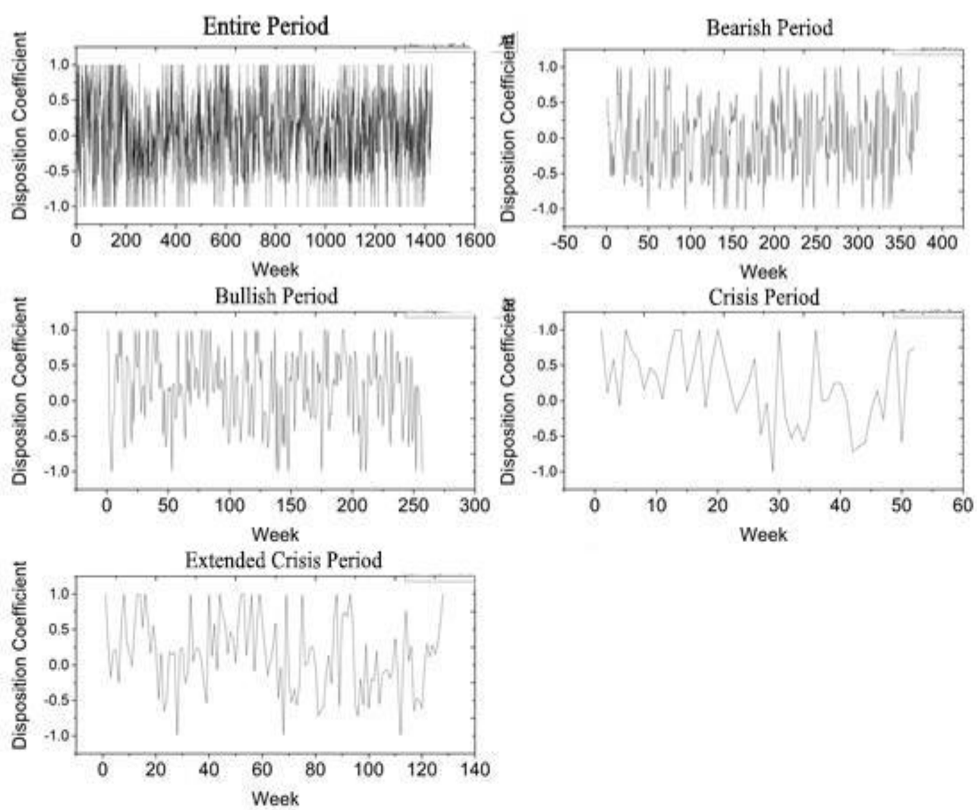


Figure 4.3 The Value of Disposition Coefficients under Different Market Conditions.

4.7 Discussion of Results

One of the comprehensively documented biases observed in the equity market through behavioral finance literature is the disposition effect. Interestingly, whether investors in the equity market display the disposition effect bias remains a thought-provoking puzzle among the academic researchers. This section provides insights into the summary of our empirical findings provided in empirical results part.

The essay records empirical evidence of relatively high disposition effect in the bullish market. The discovery of investors trading behavior that displays disposition effect in the bullish market in the Bangladesh equity market is aligned with the results of (Zhang et al. 2022; Bernard et al. 2022; Muhl & Talpsepp 2018). This could suggest that investors in our market are risk-averse and more willing to realize the winning position in the bullish market phase. The statistically significant coefficient of the disposition effect is larger for the crisis market compared to the bullish period, confirming that investors have greater tendency to display the disposition effect in the crisis market than that of the bullish market phase. The result coincides with the study of Bernard et al. (2018). We can say that modifications in the selling behavior of investors in a crisis market are brought about due to the alterations in the preferences and beliefs, which are subjected to the greater gains' realization.

Hypothesis that trading habits of market participants in selling winning stocks too soon and holding losing stocks too long are investigated with regard to different market conditions. The changing environment of the market can also present the difficulty of knowing the magnitude of the disposition effect. The market players can have different trade patterns under different market situations. What makes this study novel is that it examines the effect of the disposition effect on the frontier markets such as Bangladesh under varying market conditions such as bearish, bullish, crisis and prolonged crisis markets. The findings indicate a high disposition effect inclination in all the separate market phases except the bearish market. The disposition effect is more evident during a crisis period which is then followed by a bullish period and extended crisis period. The empirical findings reinforce the significance of examining the disposition effect across diverse market conditions in the Bangladesh capital market.

4.8 Conclusion

The disposition effect is concerned with the emotional action of investors, usually influenced by loss aversion. The essay aims to examine the hypothesis that the Bangladeshi equity market has a propensity to irrational behavior of investors to realize winning investment faster than the losing investment. No behavioral finance literature on the Dhaka Stock Exchange can match this empirical study of the disposition effect. This essay will utilize a new methodological framework of Weber & Camerer (1998) to estimate the disposition coefficients that are affected by the aggregate trading volume of the current period based on the movement of the index position of the previous day as a benchmark. The findings indicate that the disposition effect continues not only throughout the entire study period but also across the bullish, crisis, and extended crisis periods, apart from bearish period. Therefore, it is concluded that the prevalence of the disposition effect is confirmed in the Bangladeshi equity market over the application of all statistical test used in this essay analysis. It may be inferred that it has adequate evidence to signify the robust and consistent disposition effect persists even with market segmentation in the

Bangladesh equity market. The analysis further discovers that the disposition effect in the equity market of Bangladesh has oscillating effects, especially during the crisis market phase.

Chapter Five- Overconfidence Bias: A Multi-Method Approach Across Different Equity Market States

5.1 Introduction

The Classical finance strands on explicit assumption of rationality of economic agents in the decision making processes of financial markets. Each individual acts rationally and makes consistent decisions with perfect information so that he/she can maximize the expected utility. Research shows that real equity markets do not behave according to the efficient market hypothesis (EMH), the centerpiece of investors decision making framework in standard financial theory. This leads to a second reasearch dimension called the behavioral finance. It deals with the axoims of psychology to understand the actual investing decision beahvior of investors as well as the aggregate market behavior.

Since the development of behavioral finance in the late 1990s, it was apparent that the investment behavior in the equity market (irrespecive of individuals, institutionals, professional fund managers, even the academic and other researchers) is mysterious in the sense that it can not be matched with the assumptions of typical finance theories. It is not common that every market player will react to information available in the market in the same way or use the quantitative investment decisions tools in an unbiased manner. Economic agents do not adopt the axoims of rationality and their investments behavior do not constitute any normative logical choice in case of decisions under uncertainty. Rather, the investors decision-making process is influenced by their intuitive judgments, feelings, emotions, and other kinds of psychological traits that distort their economic decision outcomes and the equiy prices are represented to be far away from the fundamental values. Market anomalies are simply empirical outcomes deemed to be inharmonious with asset pricing theories in finance. Any equity market performance or outcome which can not be interpreted by the efficient market hypothesis is called financial anomaly (Silver, 2024). The some fundamental forms of anomalies may be represented as long-term underperformances of IPOs, excess volatility, momentum effcets, long-term price reversal, predictiability of future stock returns ec. This is why behavioral finance emerges as new discipline to study the human psychology about the behavior of investment characteristics. According to Ritter, the behavioral finance is developed on two fundamental premises: Cognitive psychology (the way people actually behave in their decision processes) and limits to arbitrage(the efficacy of the arbitrage opportunities under various market circumstances).

Behavioral finance theory contends that the human psychological and mental aspects of investment decisions behavior are known as behavioral biases of investors. These biases include conservatism, regret aversion, overconfidence, herding behavior, disposition effects, familarity bias, representativeness bias etc. Behavioral finance deals with human psychology to understand and explain how market participants exhibit these biases while making their investing decisions. There is no cure for these human psychology behaviors but understanding these biases to some extent can help reduce the pitfalls of complex decision making framework

There are evidences that report the investors having these psychological and cognitive biases fail to absorb and process any information accurately and have the tendency to underreact or overreact to this information, which may lead to the biased decisions (Barber & Odean 2000, 2001; Kahneman & Riepe, 1998; Raghunathan & Corfman, 2006).

Overconfidence is one of the human psychology driven prominent behavioral biases represented by the equity market participants. In simple term, it can be defined as the propensity of human being to treat themselves overconfident about their knowledge, capabilities, and perceived informaion which might lead to the incorrect investment outcomes. It is a kind of arrogant and exaggerate attitudes towards equity market decisions. Plous (1993) argue that "there is no judgment and decisions considered to be more pervasive and more potentially catastrophic than overconfidence". Based on subjective probabilities, it was observed that people have intution to overestimate the precision of their capabilities (Alpert & Raiffa, 1982; Fischhoff, Slovic & Lichtenstein, 1977).

Overconfidence hypothesis regarding security markets first introduced by Odean (1998b). Odean provides the motivation about investors psychology that the more they become overconfident, the greater will be their tendency to trade, and the lower will be their expected utility from that investments. This happens because investors generate information about how accurate they are aboiut the securities returns on the basis of misrepresented and unrelistic confidence. The consequence is that overconfident investors always carry riskier investments than rational informed investors. Barber & Odean (2013) explain that equity investors not only become overconfident about the accuracy of the private information they also overestimate their ability to analyze the information.

The puzzle of investors overconfidence observed in the financial markets produce the high market trading volume (De Bondt & Thaler, 1995; Odean 1998a, 1998b, 1999; Gervais & Odean, 2001). The opposite statement done by Varian (1989) that trading volume is completely enforced by the differences of opinions of investors. Odean (1998b) proposes that any trades, even they become insiders or the market makers can positively influence the trading volume of the market. The motivation of this trading behvaior is that they unwittingly overestimate the accuracy of the information they possess and presuming the information more reliable than the average market trend or than that of their peers.

The perseverance of overconfidence in the context of equity market investors can be explained in a manner that overconfidence makes them to become more aggressive relative to rationally behaved investors in manoeuvring the mispriced securities. This aggressive trading behavior can be traced out because of two types of investors motivation: They underestimate the ability of trading risk component and overestimate their own trading strategies.

5.1.1 Specifications of Overconfidence Behavioral Bias

In psychology, Larwood & Whittakar (1977), Svenson (1981), and Alicke (1985) were the pioneer to believe that people overestimate their ability than the market average and become more optimistic regarding the outcomes they can manage.

The new paradigm of behavioral finance spells out that excessive trading volume in the equity mrket is simply the outcome of investors' overconfidence bias. According to DeBondt & Thaler (1995), " the most probable robust finding in the psychology of judgment is that people are overconfident".

Overconfidence is one of the well admired biases observed in behavioral finance. Overconfidence posits that human being are not rational and possess some level of confidence while thay make decisions. Confidence, here, can be defined as the extent of certainty people hold about the precision of their thinking aspects (could be emotions or feelings or judgments or abilities, or perceptions). If the objective precision of the judgment of an investor is undermined by the subjective accuracy of his judgment, investor is said to be overconfident.

Overconfidence is a cognitive psychological bias driven by heuristics simplification (self-deceptiop). The term self-deception indicates that people seem to perceive that they are better than what they actually are (Trivers, 1991). People who believe that they are more calibre than their actual capabilities are termed as being overconfident-a statement defined by Psychology and Behavioral Science.

Overconfidence bias is not driven by the factors in the equity markets rather it is induced by the characteristics of market participants (Odean 1998).

Daniel et al. (1998) term overconfident investors as one who are over optimistic about the signals of their private information but not accurate about the piece of public information rceived by all market players. Overconfident investors have the tendency to overreact to any positive news coming to the market but underreact against the negative news happened. Therefore, it is evidenced that overconfidence behavior displayed by investors is nothing but the outcome of overreaction to private information and underreact to publicly disclosed information, which may represent the securities mispricing (Daniel, Hirshleifer, and Subrahmanyam (1998).

Overconfidence is the unreasonable beliefs in one's intuitive judgments or cognitive capabilities or emotional reasoning (Pompian, 2006).

5.1.2 Two fundamental Traits of investors' Overconfidence Bias regarding Investing Decisions

It seems apparent for people from all walks of life to be susceptible to overconfidence bias and they tend to possess unjustified confidence level in their capabilities and decisions. Therefore, this psychological bias may lead to the poor investing decision making. Based on the intuitive definition of overconfidence bias, the following human psychological patterns can be developed about overconfident investors in the equity market.

5.1.2.1 Overconfident Investors Taking Excessive Risk

Overconfidence will allow the equity market participants to believe that they can easily choose the winning stock. As a result, they will have the motivation to make too much investment in that particular stock, which can be represented a risky one. It is evidenced that selecting a winning stock from real investment becomes an extremely difficult task form them to execute, even for professional investor groups.

5.1.2.2 Overconfident Investors Making Excessive Trading

Investors, who are overly optimistic regarding their skills or investment strategies, will have the motivation to buy and sell stocks more frequently, which might have the adverse impact on the risk-returns characteristics of their investments in the equity market. Research document that investors who trade more often in the market are at disadvantage relative to those who go for the long-term investments.

5.2 Research Problem

The behavior of investors has long been a central concern in financial economics. The new paradigm of behavioral finance spells out that excessive trading volume in the equity mrket is simply the outcome of investors' overconfidence bias. According to DeBondt & Thaler (1995), "the most probable robust finding in the psychology of judgment is that people are overconfident". Existing research on behavioral finance challenges the assumptions of traditional financial theories by providing evidence that psychological biases systematically influence investor decision-making processes in the financial market. The overconfidence bias has emerged as one of the most prominent behavioral puzzles examined in existing literature to explain equity market anomalies in trading behavior and market performance. As a result of this cognitive distortion, investors engage in excessive trading that leads to suboptimal portfolio allocations, and underestimation of risks, which represents a deviation cannot be explained by the rational models.

The examination of overconfidence bias is especially important for frontier equity markets such as Bangladesh where investor sophistication is not high and trading is primarily retail. Retail investors usually ignore fundamental analysis as they base their judgment on personal views, rumors, and short run trends. This can cause higher market volatility and inefficiencies because their trading decisions are disproportionately affected by cognitive biases.

Despite the growing literature on overconfidence, most existing studies treat the market as a homogenous entity, overlooking the diverse emotional and psychological dynamics that arise under diverse market circumstances. Behavioral responses are rarely static; they intensify or weaken depending on the market state conditions such as boom, bear, crash, or prolonged uncertainty. Few studies have systematically attempted to examine whether overconfidence changes across market regimes such as bullish, bearish, endogenous crisis, extended crisis, and exogenous COVID-19. To fill that gap, this research tends to develop a state-dependent framework to empirically investigate overconfidence bias. Thus, it integrates insights from cognitive psychology, market microstructure theory, and empirical behavioral finance.

Despite extensive global research, there has been virtually no empirical study that explores the phenomenon of overconfidence bias in the Bangladesh equity market. The essay addresses the gap by examining whether market returns can predict trading volume as a measure of investor overconfidence, providing new insights in the context of underexplored frontier equity market**.**

5.3 Contribution of Research

The essay makes contribution to overconfidence behavioral literature in the following ways:

First, this is probably the first study to employ innovative application of information-theoretic transfer entropy measure along with advanced Long Short-Term Memory (LSTM)- a deep learning model to examine overconfidence behavioral bias in the equity markets. Unlike traditional VAR model, transfer entropy, a non-linear and non-parametric approach, is well-equipped to analyze time series data to capture true directional causality. While LSTM provides a more robust framework to identify behavioral patterns in investor activity to model sequential financial data and capture complex, non-linear, and dynamic temporal relationships between market returns and trading volumes. Second, it provides the first comprehensive empirical examination of overconfidence bias in the Bangladesh equity market, focusing on investor behavior across distinct market states, including bearish and bullish, crisis, extended crisis, and COVID-19 markets, where bearish and bullish market phases are identified by Dow Theory. It offers valuable insights into the state-dependent nature of overconfident bias by exploring how the intensity, presence, and impact of this bias fluctuate in response to changing market dynamics and investor psychology in frontier equity market environments. Third, existing literature on overconfidence bias relies primarily on aggregate market returns as a method of explaining trading volume dynamics. The psychological underpinnings of overconfidence, as shown by investors' reaction to unexpected information, may not be captured fully with this approach. This study introduces a novel method for extracting unexpected market returns by decomposing total market returns using the Market Index model and then examined for its impact on trading volume.

5.4 Theory of Overconfidence Behavioral Bias

An overestimation of the precision of the private information or the underestimation of the variances of the securities returns has been an incredible subject matter in behavioral finance literature to understand how human psychology influences the investing behavior of the equity market investors. The potential presence of overconfidence puzzle in the equity market still remains mysterious in describing why investors exposed to this behavioral bias and to what extent it impacts their trading behaviors as well as its consequences on the whole equity market behaviors.

A variety of behavioral and psychological theories explain the causes of overconfidence bias, describing the cognitive processes underlying this type of investor behavior. Behavioral finance literature delineates the possible explanations for behavioral element of overconfidence among the investors in the equity markets. This theoretical representation is systematically elaborated below.

5.4.1 Miscalibration or Overpricision (Alpert & Raiffa, 1982)

Psychological researches reveal that human decision making is subject to psychological biases. The overconfidence behavior of investors can be the reflection of their miscalibration. Miscalibration can be defined as excessive confidence regarding the precision of the received information (Alpert & Raiffa 1982, Lichtenstein et al. 1980, Ronis & Yates, 1987; Kyle & Wang 1997, Moore & Healy, 2008). Miscalibrated investors tend to overestimate their own knowledge about a particular investment or underestimate the variance of that investment. An investor is said to be miscalibre if the probability of correct outcome becomes higher than the probability assigned over the long period given the condition that all answers have a stated probability (Lichtenstein, Fischoff, & Phillips, 1980). The concept of miscalibration with two alternative definitions developed from psychology literature: miscalibration by discrete propositions and miscalibration with continuous answers.

Miscalibration by discrete propositions

There are two components to explain miscalibration with discrete answers: the subjective probability of success and the actual rate of success. By comparing these two components we can define miscalibration. This form of miscalibration can be described with the following arbitrary example.

Assume that an individual is given two alternative answers (X and Y) and asked to select one. If he states that he is 60% sure the correct answer is X. This probability is known as his subjective probability of success or the confidence level of the individual.

Now, consider how we develop the overonfidence behavior of decision makers applying the above decision component.

Suppose, S refers to the confidence level of the decision makers and is measured by the mean value of subjective probabilities given by them in the population.

We assign P as the actual rate of success answered by all the decesion makers and measured by the mean value of correct rates provided by them in that population.

Based on the above specifications, we can write overconfidence equation as:

$$O=S-P$$

If $S>P$, O becomes positive and measures overconfidence(as subjective probability is greater than the correct outcome).

If $S<P$, O becomes negative and suggests underconfidence(as confidence level is lower than the correct outcome level).

Miscalibration with Continuous Propositions

In this specification, the decision makers are not offered alternative answers to make the choice rather they are interrogated to provide the confidence intervals (mentioning that how certain they are about the specific answer they provide).

We need to understand two concepts: the surprise index (the probability of correct outcomes that lie outside the confidence interval) and the hit rate (the probability of correct outcomes that lie within the confidence intervals). The surprise index attempts to quantify the probability of true values that fall beyond confidence intervals assessed by the decision makers. The lower the confidence intervals, the higher the surprise index, and the narrower will be the decision makers confidence intervals to sufficiently justify the correct outcomes. This narrow intervals is regarded as an indicator of overconfidence. The decision makers overestimate the precision of their correct outcomes than the true values and thus provide the narrow confidence intervals.

Glaser & Weber (2007) and Broihanne et al. (2014) investigated individual investors in the equity market to assess their miscalibration behavior. In both studies, investors were requested to provide 90% confidence intervals for the correct answers. Glaser & Weber (2007) evidenced that 4 out of 5 answers given by them fall beyond 90% confidence intervals. This indicates that mean percentage of surprise index is 75% signifying thta investors are miscalibrated. On the other hand, Broihanne et al. (2014) found that on average, 5 out of 10 answers were wrong and fall outside the 90% confidence level, a clear indication of miscalibrated behavior. We know the degree of miscalibration is determined by the number of answers that lie outside the 90% confidence intervals.

In addition to above miscalibration measurement components, Broihanne et al. (2014) considered one more proposition to meausre the miscalibrated behavior of investors (both individuals and professionals) in the context of the equity market is named as returns volatility measures. Under volatility measurement, the component of the expected subjective volatility (ESV) of investors is used to assess miscalibration. If the expected subjective volatility, which is the estimated return volatility expressed by each investor, tends to become lower than the historical market volatility, investors are said to miscalibrated.

5.4.2 The Better-than-average Effects (Svenson, 1981)

The better-than-average effects is the psychological motivation that can be observed in psychology literature to explain the overconfidence bias among investors. It can be difined as people's judgmet to believe that they have greater proficiency/competency than the market average (Alicke et al., 1995; Heine & Lehman, 1997). People tend to rank their judgment in a group. Let us consider a specific example. A particular investor holding a portfolio of stocks claims that his portfolio contains the highest return among the group. But the fact is that others have the highest portfolio returns than him. It is stated that this investor has the tendency to overestimate his returns compared to the returns of others. He is judged as overconfident investor.

The better-than-average effects is the characteristics of the natural human thought proces (Taylor & Brown, 1988). They argue that any positive traits always motivate people to build their confidence and become more encouraged to engage themselves in the constructive decisions. Because human behavior is subject to cognitive thaught process that acts as strainer of information available to them.

It is the self-enhancement proneness that makes individuals to treat themselves as bettern than median individual (Greenwald, 1980). Svenson (1981) conclude from an experimental study that when individuals were asked to evaluate their capabilities, most of them exhibited that their ability/potentiality are superior relative to the median individual's abilities. Individuals always tend to display better-than-average effects or overplacement bias in their decisions.

Another way we can measure the better-than-average effects by comparing the perceived position (rank) of the individuals in a given population relative to the actual rank of the individuals. If the perceived percentile which is the subjective rank given by the individuals tends to be higher than the actual percentile, we can regard it as overconfidence behavior of individuals. In another survey conducted on university students by Larrick et al.(2007) found that the perceived percentile of students performance was greater than the actual percentile of performance. This manifests the reflection of better-than-average effects behavior of students.

5.4.3 The Ilusion of Control (Langer, 1975)

The presence of illusion of control is evidened in academic research in psychology for being overcofident by individuals in their behaviors. The illusion of control depicts that people not only overestimate their capabilities or skills but also have the tendency to overstate their ability to control over the chances of success. The illusion of control intutively holds an inaccurate perception about the human behavior that they have strong control over their life than they actually can. When the expected probability of an individual success perceived to be inappropriately higher than what objective probability represents, it symbolizes the illusion of control (Langer, 1975).

The illusion of control and the notion of control are negatively correlated. The low probability of illusion of control behavior is supported for the high control level attempts and the presence of high probability of this behavior observed when individuals control level become low.

Burger (1986) in a study considered a specific human characteristics known as desirability of control and found that individuals who express more desirability of control are represented by strong illusion of control behavior.

5.4.4 Self-Attribution Theory (Langer and Roth ,1975)

This theory explains how people interpret their successes and failures as a result of their own actions. People have the tendency to attribute success to internal factors like own skills, intelligence, and failures in external circumstances such as market conditions and bad luck (Langer & Roth 1975; Taylor & Brown 1988; Daniel et al., 1998). It's common for investors to attribute their profits to their own intelligence or strategy when they make a profitable trade in the financial markets. Whenever they suffer losses, they blame external factors such as news events or market manipulation. Overconfidence results from this bias because successes are seen as proof of skill, while failures are dismissed, resulting in excessive trading and excessive risk taking.

5.4.5 Dynamic Learning Theory (Gervais & Odean, 2001)

Dynamic learning theory suggests that learning is a continuous, evolving process impacted by previous experiences and changing market scenarios. The intuition is that learning is a dynamic concept, and changes over time in response to context and feedback. Investors in the equity market gradually build up confidence as they experience early success in their trading behavior. They have the tendency to attribute success to their ability rather than bad luck, which ultimately inflates overconfidence. This process of learning encourages investors to trade frequently and reinforces overestimation of abilities. This theoretical underpinning illustrates how and why overconfidence bias prevails and persists in equity markets.

5.4.6 Limited Attention Theory (Barber, Lee, Liu, & Odean, 2010)

Limited attention is a theory from behavioral finance that urges people unable to process all available information in the market, particularly in information-based environments like financial markets, because they have limited cognitive resources. Investors lack the ability to focus on everything. Rather, they deliberately pay attention to what appears to be most important or noteworthy at a given time. Investors in equity market are flooded with information, such as earnings announcements, news stories, macro indicators and therefore, may disregard relevant information, which could result in suboptimal decisions.

More noticeable events like extreme equity price changes, media coverage, tend to draw greater investor attention and could be overemphasized when making decisions. A noisy and fast-growing equity market may provide opportunities for investors to misread market signals, overestimate their understanding, and exhibit overconfidence due to information overload and attentional restrictions.

The above theories are developed from broader psychological and social fields to understand why market participants in the financial market act overconfidently in their investment decision-process. These theories are presented in combination describing the cognitive processes underlying this type of investor behavior, called overconfidence puzzle.

Through a network of cognitive processes, these psychological theories represent a broad spectrum of approaches to overconfidence bias in financial markets. These theories help explain realizing that overconfidence is not a mere random mistake, but a systematically predictable psychological bias. The diagram of the conceptual framework demonstrates how these psychological underpinnings together contribute to overconfidence bias, which influences observable market behavior through excessive trading volume.

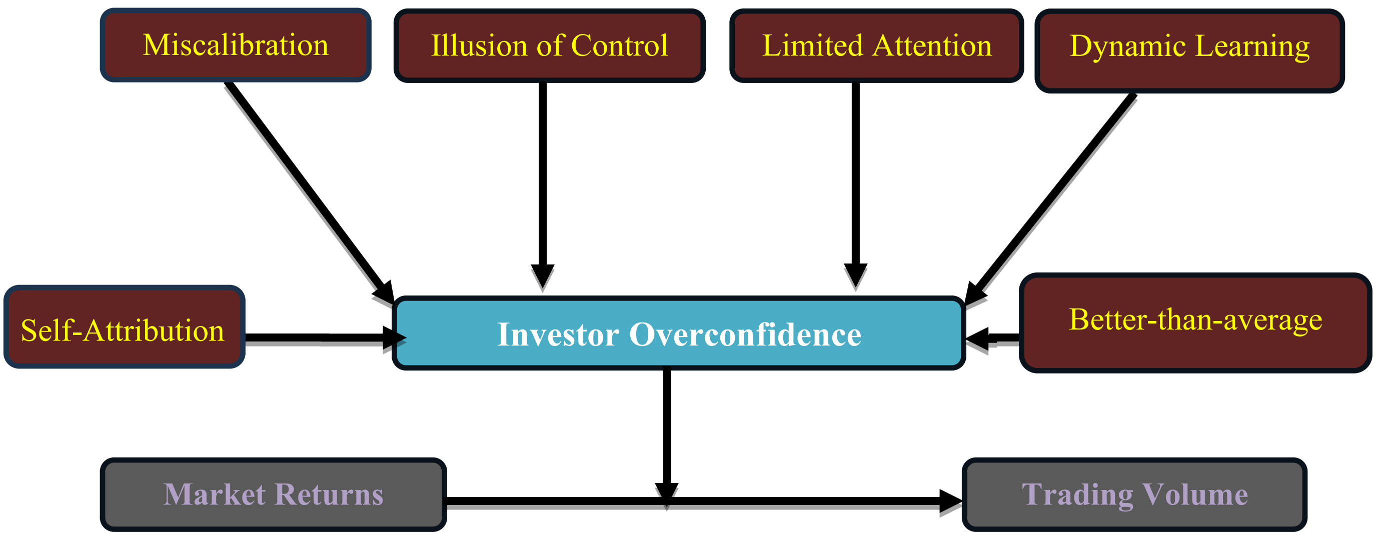


Figure 5.1: Theoretical Underpinnings and Conceptual Framework for Investor Overconfidence

The diagram highlights the aggregate market returns as an important stimulus in the investor behavioral process. When market returns increase, investors become more confident in their decision-making skills and will, therefore, trade more. The behavior of overconfidence can vary across market states - bullish, bearish, or crisis - and can be better understood in the context of the various emotional and informational pressures to which it is exposed. In this way, framework does not only connect theory with behavior but also provides a systematic basis of empirical testing, showing the dynamic relationship between the market returns, and trading activities as a manifestation of investor overconfidence in a frontier market like Bangladesh.

5.5 Empiricial Studies on Overconfidence Bias

Behavioral finance literature demonstrated significant evidence in favor of numerous biases among investors in their decision making in the context of the equity market. One of the behavioral biases exhibited by equity market participants was widely investigated by different researchers and scholars is overconfidence bias.

This section attempts to narrate the empirical studies on overconfidence behavioral bias according to whether the research is conducted using econometric methodologies across global equity markets.

As a theoretical basis for explaining market under- and overreactions, Daniel, Hirshleifer, & Subrahmanyam (1998) proposes two psychological biases: investor overconfidence in the accuracy of private information and biased self-attribution, where investors adjust confidence asymmetrically based on success or failure. The model predicts a number of key market anomalies, including under-reaction to long-term returns, overreaction to short-term momentum, excess volatility, and earnings drift. The study also links return predictability to managerial behavior and public events.

Overconfidence has a significant impact on financial market outcomes, but the effects vary depending on who is overconfident and how information is disseminated. Odean (1998) examines a market structure with price-taking traders, a strategic insider, and risk-averse market makers, all these can potentially lead to overconfidence. They found that overconfidence increases expected trading volume and market depth but reduces expected utility. A key characteristic of overconfidence is that it causes the market to underreact to rational information, while overreacting to salient and anecdotal cues, thus destabilizing price efficiency and volatility.

A key explanation for excessive trading in equity markets is investor overconfidence. Traders who are overconfident tend to trade more often, believing they have superior judgment or information. Trading costs can erode gains developed from this behavior, resulting in suboptimal investment outcomes. According to Odean (1999), a study using trading data from 10,000 individual accounts found that investors bought more securities than they sold, challenging the notion that overconfidence necessarily leads to poor decisions. As a result of this surprising result, overconfident investors may still possess some predictive power for stock selections even when they trade too frequently.

Barber & Odean (2000) examined the trading records of 66,465 households from 1991 to 1996 and found that the most active traders underperformed the market, earning an average annual return of only 11.4% compared to 17.9% for the market as a whole**.** Despite earning 16.4% on average, households traded frequently and concentrated on their holdings in high-beta, small-cap, and value stocks. The study highlights how overconfidence leads to high trading activity, which in turn leads to poor investment performance.

The multi-period market model developed by Gervais & Odean (2001) incorporates traders' learning over time about their own abilities**.** As a result of over-attributing success to skills, traders tend to be overconfident in early stages of their trading careers. Increasing self-assessment bias leads to increased trading volume and volatility, as well as deviations in expected prices and profits. With experience, traders' self-perception becomes more accurate, and overconfidence declines. In addition, the model explains dynamic patterns in market activity linked to learning and overconfidence through behavioral explanations.

A study by Barber & Odean (2001) examined investors overconfidence behavior analyzing account data from over 35,000 households within the period 1991–1997. The study finds that men trade 45% more than women, and that excessive trading results in significantly lower net returns. Especially, trading lowers men's returns by 2.65 percent annually, while women's returns are lowered by 1.72 percent. these results confirm the prediction that trading behavior is negatively influenced by overconfidence, particularly among men.

The study by Chuang & Lee (2006) included all the companies listed on NYSE and AMEX over the period January 1963 to December 2001 to analyze the investors overconfidence behaviors. The study tested the four overconfidence hypotheses usnig the aggregate market data. First, overconfident investors tend to overreact to private information and underreac to publicly access information. Second, Positive market trend will enable overconfident investors to trade more in the following period. Third, Excessive trade done by overconfident investors will create more market volatility. Four, Overconfident investors tend to underestimate the risk and engage trading in riskier stocks. Empirical results confired the presence of all four hypotheses in the US equity market.

Statman (2006) empirically tested overconfidence bias in the US equity market using monthly data on all New York Stock Exchnage/American Stock Exchnage common stocks for the period August 1962 to December 2002. They used vector autoregression and impulse response functions to assess whether the level of investor overconfidence to change with past market returns. Research results indicate that individual trading volume has positive association with past aggregate returns and with lagged individual security returns, an indication of the presence of investor overconfidence. They also report that investor overconfidence is more pronounced in case of small capitalized stocks compared to large-cap stocks.

An experimental research was conducted by Trinugroho and Sembel (2011) to measure the invesotor overconfidence in Indonesia. The experimental results show that investors who are overconfident make more trading than investors having low overconconfidence. Thus, the high overconfident investors generate lower returns from their investment than the low overconfident investors. One more finding, the influence of bad news does not affect the trading volume of high overconfident investors between pre and post news periods. Whereas, the trading activity declined in post bad news case for low overconfident investors.

Prosad et al. (2017) empirically examine the presence of both disposition effects and overconfidence in the Indian equity market using daily dataset from 2006- 2013. They employed bivariate and trivariate vector autoregression (VAR) methods and impulse response function (IRF) on the aggregate NIFTY 50 index return and individual returns. The study reports the presence of both overconfidence and disposition effects biases in the Indian equity market for the whole sample period. They also provided the presence of these two biases by segregating 20 individual companies among companies in the NIFTY 50 index. Lastly, it reports dominance of the overconfidence bias over the disposition effects in the context of Indian market.

Metwally & Darwish (2015) studied whether overconfidence behavioral bias presents in the equity market of Egypt during the period 2002-2012. They split the study period into four sub periods: two positive trend market states and two negative trend volatile periods. The study applied econometric methodology of Vector Auto Regreesion and Granger Causality test to examine the relation between aggregate market returns and market turnover and found the significant evidence that investors in the Egyptian equity market are overconfident.

Zia, Sindhu & Hashmi (2017) studied overconfidence behavior in Pakistan equity market to investigate the lead-lag relationship between market returns and market turnover over the period 2005-2013. The results document that market turnover directly depends upon the past equity market return, which indicates that investors in Pakistan equity market are overconfident. Furthermore, the impulse response function also supports the presence of overconfidence bias confirming that the response of market turnover to market return is higher than the response observed in the opposite direction. The findings may bring important implications for investors and other market players to design appropriate trading strategy for the investment decision process.

Kusuma & Arfianto (2018) studied a survey questionnaire based on 150 investors in Semarang, Indonesia to identify the different cognitive components of overconfidence in their financial decisions. Questionnaire designed to include 30 questions representing the miscalibration, the better-than-average effects, the illution of control, and the unrealistic optimism behavior of investors and results suggest that all these components except unrealistic optimism have positive and significant effect on overconfidence behavior related to investors' investment decisions.

The overconfidence behavior of investors at Bombay Stock Exchange examined by Mushinada & Veluri (2018) for the sample period April 2004 to March 2012. They applied bivariate vector autoregressions and EGARCH models to identify whether overconfidence bias exists among investors in Indian equity market. Empirical findings documented the presence of overconfidence bias among investors observed because of their self-attribution behavior in the market. The excessive trading made by the overconfident investors ultimately represented the observed high volatility phenomenon.

Alsabban & Alarfaj (2020) empirically examine investor's overconfidence behavior in the Saudi stock market, Tadawul. The data used for the study spanning 2007 to 2018, monthly based. It is hypothesized that positive past market returns influence the level of investors' overconfidence leading to higher trading turnover in stock markets. To test for overconfidence behavior, a market-wide Vector autoregression (VAR) model is designed to analyze the lead-lag relationship between market returns and market turnover. The results obtained suggest that investors in the Saudi stock market are overconfident.

Phan et al., (2020) investigated overconfidence bias in Vietnam, Thailand, and Singapore equity markets over the period from January 1, 2014 to December 31, 2018. They adopted Granger Causality and VAR approach to find evidence of the overconfident effect in these equity markets. Clear evidence of overconfidence bias was found in both Vietnamese and Singaporean markets, in which Singaporean investors show higher degree of overconfidence than Vietnamese investors. Overconfidence is not as clear in Thai market, however a direct causal link from increased returns to increased investor confidence was found. The results shed lights into the existence of overconfidence bias in Vietnam, Thailand, and Singapore on a comparative basis, which provide more insights and implications for future research in this new and rising field of research.

Azam & Baig (2023) empirically analyzes the presence of overconfidence bias using the Nifty 50 Shariah index in the Indian stock market for the period January 2001-December 2020. The study used daily data of two endogenous variables; market returns and market turnover to find the relationship between them. Using vector autoregression (VAR) model, they find that market return does not influence market turnover while market turnover does influence market return. It is observed that two exogenous variables of return volatility and exchange rate have positive influence on other endogenous variables.

Evidence of overconfidence behavior was tested by Seraj et al., (2022) in the Saudi stock using the survey data from 180 respondents. They applied partial least squares structural equation model (PLS-SEM) and examined relationship between financial literacy and investment decisions through mediating effect of overconfidence. Results reveal that investor decisions were influenced by overconfident behavior with financial literacy and investment behavior were positively moderated by overconfidence.

Azam et al., (2022) investigate the overconfidence bias at sector levels in the Indian equity market during COVID-19 period. The study uses daily data from 1 January 2015 to 31 December 2020. Adopting VAR model, findings show that in the pre-COVID-19 phase overconfidence bias is more prevalent in all the cyclical sectors, but it is not found significant for the defensive sectors. In the COVID-19 period, all the cyclical sectors display overconfident trading behavior. In the case of defensive sectors, overconfidence of investors is more pronounced in the Pharma sector. It is identified that Energy is the only sector that remains unaffected from overconfidence bias in both the periods.

Ganesh et al., (2022) employed vector autoregression (VAR) and impulse response function (IRF) methodologies to examine the influence of overconfidence bias in the Indian equity market and find strong evidence in favor of it for the whole market as well as during periods of market stress like global financial crisis of 2007-2008, and COVID-19 pandemic period. They used daily data of Nifty 50 index spanning from April 2005 to March 2022 obtained from National Stock Exchange of India.

Kuranchie-Pong & Forson (2022) investigates whether there is evidence of the overconfidence bias in the Ghana stock market applying pairwise Granger causality. The results reveal a unidirectional Granger causality that exists between weekly market returns and weekly trading volume during the COVID-19 pandemic period, which evidences the presence of the overconfidence bias. In addition, the study employs GARCH (1,1) and GJR-GARCH (1, 1) models to identify whether overconfidence bias has played a role in the volatility. The estimated conditional variance results indicate that the excessive trading conducted by overconfident market participants significantly contributes to the weekly volatility observed throughout the COVID-19 pandemic period.

Kumar & Prince (2022) attempted to test investors' overconfidence bias in the Indian equity market in different market periods: pre-crash period (2006-2010), crash period (2008-2010), and post-crash period (2010-2021). They used the data period from 2006 to 2021 and applied the vector auto regression (VAR) and impulse response function (IRF). Findings reveal that investors in the Indian market were overconfident during pre-crash period, but they were not found overconfident in post-crash period.

Bouteska et al. (2023) investigate the presence of overconfidence in the US equity market by studying the causal relationship between return and trading volume covering the period from January 4, 2016, to August 31, 2021. They employ VAR and multilayer neural network nonlinear approach on daily returns and trading volumes of the S & P 500 index. The results present evidence of overconfidence among investors in the US market. However, there is a decline in the rate of returns during the study period, implying uncertainty caused by the COVID-19 pandemic.

Shrotryia & Kalra (2023) studied the overconfidence bias in 46 global equity markets during pre-COVID-19 and COVID-19 periods over the period from July 2015- June 2020. Market-wide vector auto regression (VAR) and impulse response function (IRF) have been utilized in the study. Findings report a highly significant positive coefficient for most of the lags in Japanese, US, Chinese, Vietnamese equity markets in the pre-COVID-19 era. In COVID-19 phase, study finds strong overconfident behavior in the Chinese, Taiwanese, Turkish, Jordanian, and Vietnamese equity markets. It is observed that none of the developed equity markets reveal overconfident behavior during both phases.

Rabbani et al., (2024) examines G7 stock market overconfidence bias before and during COVID-19 using daily data from 2015-2021. applying vector autoregressive (VAR) and impulse response functions (IRFs) found positive correlations between trading volume and returns in Canadian and Italian markets before COVID-19, with overconfidence evident in Italy during the pandemic. Additionally, market liquidity affects overconfidence, highlighting important implications for investors and regulators.

Mahjoubi & Henchiri (2024) investigated whether investors overconfidence impact the level of market efficiency in 21 developed and 25 emerging equity markets over the period from January 2006 to June 2020. By following the transaction volume decomposition approach of Chuang & Lee (2006), they found that overconfidence does not influence market efficiency in any of the countries. They attributed the findings due to different crises like the subprime crisis, the euro zone crisis, the stock market crash in China or COVID-19 crisis reduced investor confidence.

Dhingra & Yadav (2024) investigated whether overconfidence bias exist for the Indian exchange-traded funds (ETFs) focusing on a sample of 12 equity ETFS in both pre and during COVID-19 pandemic. They applied vector auto regression (VAR) and impulse response functions (IRFs) and found that investors in Indian ETFs market are overconfident, even in both crises' periods. This finding brought implications for market participants, policymakers, and asset management companies.

5.6 Hypothesis Development

Behavioral finance is primarily concerned with understanding investor behavior, especially how investors' psychology influence trading decisions. Overconfidence is one of the most influential biases, characterized by the tendency of investors to overestimate their knowledge, predictive skills, or control over a market outcome (Barber & Odean, 2001). Traders who are overconfident often trade more frequently, especially when they believe past performance validates their judgments, leading to mispricing and excessive volatility in the market (Odean, 1998; Barber & Odean, 2001).

In particular, overconfidence is inferred from the impact of past market returns on current trading volume, based on the established logic that excessive trading signals belief in investor's predictive capability about market movements (Gervais & Odean, 2001; Daniel et al., 1998).

Overconfidence has been thoroughly analyzed in behavioral finance literature. Numerous studies have adopted VAR model to investigate the dynamic lead-lag relationship between market returns and trading volumes. Empirical study by Statman et al. (2006) has been considered a foundational framework to assess whether past market returns significantly predict future trading volumes, an indicator of overconfidence bias. Since then, this framework has been adopted in a variety of market settings. This foundation has led to a substantial number of studies examining market-wide overconfidence across markets and time periods. These empirical studies include Zia et al. (2017); Phan et al. (2020), Metwally & Darwish (2015), and Prosad et al. (2017); Kumar & Prince (2022); Ganesh et al., (2022); Shrotiya & Kalra (2023); and Mahjoubi & Henchiri (2024) across developed, emerging, and frontier markets.

Against this backdrop, this essay formulates the following main hypothesis to empirically examine whether overconfidence bias exists in the Bangladesh equity market:

H1: Past market returns significantly influence subsequent trading volume, indicating the presence of overconfidence bias among investors across different market states.

An important element of this hypothesis is grounded in the overconfidence theory from behavioral finance, which says that investors tend to overestimate their private information or predictive abilities (Odean, 1998; Gervais & Odean, 2001). Therefore, they trade more aggressively following gains and losses in the market, believing they accurately predicted these movements.

Investors' behavioral responses are hardly uniform across the different market scenarios. Investor psychology may be state-contingent, with emotions like optimism, fear, and uncertainty exerting different levels of cognitive distortion on decision-making processes depending on overall market environment. Therefore, examining overconfidence without accounting for heterogeneous market states may obscure crucial variations in its operation. This study uses a market-state-dependent framework to classify equity markets into bullish, bearish, endogenous crisis, extended crisis, and COVID-19 market states. Each of these states may reflect varying levels of sentiment, risk perception, and information asymmetry-all of which can increase or decrease overconfidence.

Following this framework, we develop the following sub-hypotheses to test whether and how the influence of past returns on trading volume changes systematically within and across these states. Besides enhancing the behavioral realism of the analysis, this approach contributes to the growing literature on contextual and regime-sensitive investor behavior, particularly for a frontier equity market like Bangladesh.

H1a: Overconfidence bias is more pronounced in bullish markets than in bearish markets.

The behavioral finance theory suggests that investor sentiment varies with the direction of the market. During bullish markets, rising prices reinforce investors' belief in their own forecasting abilities, fueling overconfidence and self-attribution, which is the hallmark of overconfidence hypothesis (Gervais & Odean, 2001). Investors tend to become more cautious in bearish markets due to loss aversion and increased risk sensitivity, which often suppress overconfidence. As a result, it proposes that past returns have a stronger influence on trading volume in bull markets compared to bear markets, which is a proxy for overconfidence.

H1b: Overconfidence bias is present during endogenous crisis periods, but its pattern differs from non-crisis states. (Glaser & Weber, 2007; Kim & Nofsinger, 2008).

During endogenous crises (crashes originating within the market), certain investor groups may maintain or even intensify overconfident trading due to the illusion of control or the belief that they can time the market (Daniel, Hirshleifer, & Subrahmanyam, 1998). Investors continue to trade heavily, misinterpreting sharp price movements as trading opportunities rather than signals of systemic risk.

H1c: Overconfidence bias persists during extended crisis periods, although its intensity may vary over time. (Barberis, 2013; Gervais & Odean, 2001).

In extended crises, when market stress persists over months, investors may initially retreat but usually return to overconfident behavior as they grow desensitized to prolonged uncertainty. According to adaptive expectation theory, investors gradually form biased expectations because of partial market recovery or false confidence in stability.

*H1d: Overconfidence bias weakens during exogenous crisis periods like COVID-19 due to heightened uncertainty and lack of control. (*Kuranchie-Pong *& Forson, 2022).*

An exogenous crisis (such as COVID-19) introduces unpredictable nonfinancial shocks that limit the ability of investors to form rational or overconfident expectations. According to ambiguity aversion literature (Ellsberg, 1961), when the source of risk is unknown, investors become more cautious and reduce speculative trading, disrupting typical overconfident mechanisms.

5.7 Data and Methodology

5.7.1 Data

The study investigates overconfidence bias in the Bangladesh equity market using on daily data from the Dhaka Stock Exchange (DSE) spanning from January 01, 2010 to December 31, 2021. The data set incorporates closing prices and trading volumes of all listed companies on the Dhaka Stock Exchange (DSE) after excluding missing or suspended stocks. We calculated adjusted returns to control the effects of corporate actions of dividends and bonus shares announcement. Market return is calculated by averaging the daily return of all listed stocks traded on each day, which is termed as equally weighted market return on each trading day. While the market trading volume is determined by summing up the trading volume of all stocks each day. Similarly, equally weighted industry market returns are also calculated by averaging the daily return of all stocks for each industry, and industry trading volume is calculated by summing up the daily trading volume of all stocks belonging to each industry.

5.7.2 Methodology

The essay employs a multi-method approaches to investigate investors overconfidence in the Bangladesh equity market such as Vector Autoregressive (VAR), transfer entropy, and long short-term memory (LSTM). We combine a traditional econometric model with informatic entropy and advanced machine learning tools. This methodological innovation provides a unique and robust framework to examine overconfidence bias across diverse market states like bearish, bullish, crisis, extended crisis and COVID-19.

5.7.2.1 Vector Autoregressive (VAR) Model

Vector autoregressive is a fundamental econometric framework empirically used to assess the linear interdependencies among different time series variables and reflect the dynamic representation of their interactions. In the VAR system, all variables are treated as endogenous indicating that each variable is explained by its own lag value and the lag values of all other variables. The VAR model is considered as a useful tool for measuring the direction of causality among the variables in the system.

The Standard VAR Model Specification:

The general VAR model of order p for n variables can be specified as:

$$M_t = \alpha + \sum_{i=1}^{p} \gamma_i M_{t-1} + \mu_t \tag{5.1}$$

or alternatively dynamic relationship for multivariate VAR(p), vector autoregression of order p can be presented as

$$M_t = \alpha_0 + \gamma_1 M_{t-1} + ...+ \gamma_\rho M_{t-\rho} + \varepsilon_t \tag{5.2}$$

Where,

M_t is the n x 1 vector of endogenous variables at time t

α is the n x 1 vector of constants

ρ is the order of the VAR

γ_i captures the dynamic relationship of n x n coefficient matrices

μ_t is the n x 1 vector of error terms with the condition that:

$E[\mu_t] = 0$ and $E[\mu_t \mu_t^!] = \sum \mu$, and no autocorrelation

$E[\mu_t \mu_{t-k}^!] = 0$ for $\kappa \neq 0$

Bivariate VAR (Vector Autoregressive) model specification:

The VAR model for two variables, market returns and market trading volume, can be developed as follows:

$$TV_t = \alpha_1 + \sum_{i=1}^{p} \beta_{11,i} MR_{t-1} + \sum_{i=1}^{p} \beta_{12,i} TV_{t-1} + \sum_{i=1}^{l} \gamma_{13,i} CSAD_{t-1} + \sum_{i=1}^{l} \gamma_{14,i} VOL_{t-1} + \varepsilon_{1,t} \tag{5.3}$$

$$MR_t = \alpha_1 + \sum_{i=1}^{p} \beta_{21,i} TV_{t-1} + \sum_{i=1}^{p} \beta_{22,i} MR_{t-1} + \sum_{i=1}^{l} \gamma_{23,i} CSAD_{t-1} + \sum_{i=1}^{l} \gamma_{24,i} VOL_{t-1} + \varepsilon_{2,t} \tag{5.4}$$

Where,

α_1 and α_2 are the constant terms

$\beta_{i,j}$ and $\gamma_{i,j}$ are the coefficients representing the relationship

TV_t is the market trading volume and MR_t is the equity market return calculated as the weighted average return of the individual stocks listed on the DSE.

$CSAD_t$ is the cross-sectional standard deviation and Vol_t represents return volatility used as exogenous variables.

$\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms in the model

ρ is the optimal lag length

The null hypothesis in the model states that MR_t does not Granger cause TV_t tested using the lagged coefficients of MR_t in the TV_t equation. Similarly, a reverse test is examined for TV_t Granger causing MR_t.

The reliability of VAR estimation requires the variables in the system to be stationary, and the error terms need to be serially uncorrelated, homoscedastic. The selection of optimal lag order for each endogenous variable is essential for VAR model accuracy. This is usually determined using lag selection criteria like Akaike Information Criterion (AIC), Schwarz Information Criterion (BIC).

5.7.2.2 Impulse response function (IRF)

An impulse response function (IRF) is a fundamental concept in the context of vector autoregressive (VAR) model to explore the dynamic behavior of a one-time shock (innovation) in one variable and its effects on all other variables in the system over time. It traces the reaction of how one unit shock to MR_t impacts TV_t and how long this impact persists, and the vice-versa. IRF enables us to identify how shock in one variable propagates through other variables in the system over subsequent periods by analyzing the magnitude of the response, its duration effect, and the direction of the response.
IRFs model specification

The impulse response function (IRF) can be derived from the general VAR framework with its transformation into moving average (MA) representation. The model looks like:

$$Y_t = \mu + \sum_{i=0}^{\infty} \varphi \mu_{t-1} \tag{5.5}$$

μ is the mean of the series

φ is the error term or innovation (shock)

φ indicates impulse response metrics. It measures how innovation at time t impacts the variables at time t+i. Every component of φ shows the response of shock in one variable and its influence on other variables after i periods.

Once the causality is established between the variables considered in the model, IRFs may help policymakers identify and formulate desired policy aspects. For example, if equity market return can significantly influence trading volume, market trading activity may signal heightened investor sentiment, which ultimately captures the underlying market dynamics.

5.7.2.3 Transfer Entropy Model

Transfer entropy is a non-parametric information-based approach used to detect the direction of information flow between two time series variables. It is a measure of statistical causality in the same sense as Granger Causality does. The standard Granger-causality test assumes a linear functional form in which the causes and effects are determined and is implemented by fitting autoregressive models (Granger, 1969; Wiener, 1956).

Transfer entropy, proposed and applied by Schreiber (2000) is treated as an essential tool of assessing causal relationships in nonlinear systems (Hlavácková-Schindler et al., 2007). It quantifies the directional and dynamical information flow between two interacting time series (Montalto, 2016) without assuming any functional form.

Transfer entropy is developed relying on the concept of Kullback-Leibler distance under the assumption that the underlying series are Markov Process. A stationary Markov Process is a stochastic process used in time series analysis in which statistical properties remain constant over time, and the probability distribution of the future state depends on its current state, not on the sequence of preceding states.

Entropy definitions can be explained in terms of Shannon and Renyi entropies with a slight variation in their properties. Shannon entropy possesses all desired properties of an information measure that seems to be most appropriate for the distributions of financial variables (Hlavácková-Schindler et al., 2007). Assume that X is a discrete random variable, can take values $x_1, x_2, \ldots\ldots\ldots, x_m$ with corresponding probability $p_i, i = 1,2,3,\ldots\ldots\ldots\ldots\ldots\ldots\ldots, m$. The Shannon entropy is an average amount information gained from a particular investment value,

$$\mathrm{H}(X) = -\sum_{i=1}^{m} p_i \log p_i \tag{5.6}$$

The joint entropy $\mathrm{H}(X,Y)$ of the random variable is defined as

$$\mathrm{H}(X,Y) = -\sum_{i=1}^{m_X}\sum_{j=1}^{m_Y} p(x_i, y_j)\log(p(x_i, y_j)) \tag{5.7}$$

Where, $x_i, i = 1,2,\ldots\ldots\ldots, m_X$ the values of the discrete variable X,

$y_j, j = 1,2,\ldots\ldots\ldots, m_Y$ the values of the discrete variable Y, and

$p(x_i, y_j)$ the joint probability that X is in state x_i and Y is in state y_j

The joint entropy is expressed in terms of conditional entropy $\mathrm{H}(Y|X)$:

$$\mathrm{H}(Y|X) = \mathrm{H}(X,Y) - \mathrm{H}(Y) \tag{5.8}$$

In discrete case, the conditional entropy is equal to:

$$\mathrm{H}(Y|X) = \sum_{i=1}^{m_X}\sum_{j=1}^{m_Y} p(x_i, y_j)\, p(y_j|x_i) \tag{5.9}$$

Where, $p(y_j|x_i)$ denotes conditional probability.

The theoretical motivation for employing the transfer entropy approach to measure the causality of how one variable influences the other may stem from the model's ability to capture asymmetric and non-linear relationships. Equity market variables usually exhibit intricate and non-linear relationships that traditional causality models fail to detect. Transfer entropy, however, does not presuppose any specific distributional form of time series data ideally suited to capturing non-linear interactions, and thus is more robust to measure causality analysis for financial time series.

Mathematical Development of Transfer Entropy

Schreiber (2000) describe the Shannon transfer entropy model for given two time series X_t and Y_t to measure information from X to Y as:

$$T_{X\to Y} = \sum_{y_{t+1},y_t,x_t} p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1}|y_t, x_t)}{p(y_{t+1}|y_t)} \tag{5.10}$$

Where,

$p(y_{t+1}, y_t, x_t)$ is the joint probability distribution of the future state y_{t+1}, the current state y_t, and x_t

$\rho(y_{t+1}|y_t, x_t)$is the conditional probability of y_{t+1} given the past information y_t, and x_t.

$\rho(y_{t+1}|y_t)$ is the conditional probability of y_{t+1} given the past information y_t, .

Transfer entropy measures the amount of uncertainty in Y_{t+1} that can be reduced by knowing the past information of X_t in addition to Y_t. If X has a causal effect on Y, knowing X_t should significantly reduce the uncertainty about Y_{t+1}, producing a higher transfer entropy value.

To measure the direction of causality from equity market return to market trading volume, we can present the transfer entropy model as

$$T_{MR \to TV} = \sum_{TV_{t+1}, TV_t, RM_t} P(TV_{t+1}, TV_t, RM_t) log \frac{P(TV_{t+1}|TV_t, RM_t)}{P(TV_{t+1}|TV_t)} \quad (5.11)$$

$$T_{TV \to MR} = \sum_{RM_{t+1}, RM_t, TV_t} P(RM_{t+1}, RM_t, TV_t) log \frac{P(RM_{t+1}|RM_t, TV_t)}{P(RM_{t+1}|RM_t)} \quad (5.12)$$

The equation 5.11 describes the causality from market return to trading volume whereas, the equation 5.12 defines the causality from trading volume to market return. The other representations mentioned in equation remain same.

Transfer entropy is capable to accommodate asymmetric relationship, i,e., $T_{R_m \to TV} \neq T_{TV \to R_m}$ and thus it enables to quantify the directional coupling between two variables. The net information flow can be defined as

$$TE = T_{R_m \to TV} - T_{Tv \to R_m} \quad (5.13)$$

This quantification represents the dominant direction of information flow. This means a positive transfer entropy value indicates a dominant information flow from market return to trading volume compared to the other direction or similarly which variable provides more predictive information about other variables in the system (Michalowicz, Nichols, & Bucholtz, 2013).

Effective Transfer Entropy

Effective transfer entropy is the refined version of transfer entropy designed to measure causal inference while accounting for the confounding effects of shared sources of information and spurious correlation, which might reduce the overestimation of the causality direction. The standard transfer entropy may provide bias estimate due to small sample size or influence of common external factors, and this can be corrected by effective transfer entropy.

Mathematically, Effective transfer entropy can be formulated as

$$ETF_{Y \to X} = TE_{Y \to X} - TE_{Y_{Shuffled} \to X} \quad (5.14)$$

Where, $TE_{Y_{Shuffled} \to X}$ is the shuffled Y series. This shuffling is carried out by randomly drawing individuals from Y series and developing a new series, which makes sure that the dependencies between X and Y and the shuffled series are destroyed. $TE_{Y_{Shuffled} \to X}$ converges to zero when sample size increases and non-zero with small sample effects. Effective transfer entropy confirms consistent estimation by shuffling the data several times and computing the average transfer entropy over the simulated times. This shuffled transfer entropy value is subtracted from the transfer entropy value to generate a bias-corrected effective transfer entropy estimation.

Adoption of transfer entropy approach to measure the direction of causality between equity market variables may provide insights into complex and non-linear interactions of market variables, enabling them to understand the level of market efficiency and the dynamics of investor psychological behavior.

5.7.2.4 Long Short-Term Memory (LSTM) Model

To examine overconfidence bias, the study employs Long Short-Term Memory (LSTM) model to analyze the correlation between market returns and market trading volumes. Since overconfident investors tend to trade more frequently after observing unanticipated market gains, it is hypothesized that past market return can predict future trading volume. The LSTM, a special variant of recurrent neural network, is constructed to process time-series data by discovering long-term dependencies. Unlike standard econometric models that impose linear assumptions and predefined lag structures, LSTM is ideally suited to equity market variables where it can learn intricate, non-linear patterns, and adapt to dynamic market environments.

The LSTM-based prediction model

To predict market trading volume based on past market returns, the following LSTM formulation is developed:

$$TV_t = f_{LSTM}\,(R_{t-1}, R_{t-2}, R_{t-3}, \ldots\ldots\ldots. R_{t-n}) \qquad (5.15)$$

Where, TV_t the predicted trading volume at time t.

f_{LSTM} the function learned by the LSTM network, which captures the sequential patterns in historical market returns.

$R_{t-1}, R_{t-2}, R_{t-3}, \ldots\ldots\ldots. R_{t-n}$ the sequence of past market returns used as input in the LSTM framework.

N refers to the selected number of time window or lag length generated by the LSTM.

If LSTM model demonstrates strong predictive ability, implying that investors overreact to past market returns and producing increased trading activity, which supports overconfidence theory.

The LSTM works with two separate model development.

Model 1: Baseline Model (Only Trading Volume).	Model 2: Augmented Model (Trading Volumes + Market Returns)
Inputs: Lagged trading volumes, Outputs: Predicted trading volume Objective: This model is used as a benchmark for comparison.	Inputs: Lagged trading volume and lagged market returns Output: Predicted trading volume The objective is to examine whether the inclusion of past returns significantly improves the prediction accuracy, suggesting the presence of

	overconfidence bias.

If Mean Squared Error (MSE) becomes lower under the Restricted model relative to the Baseline model, we confirm that market returns have predictive information about trading volume, supporting the presence of overconfidence bias.

Estimation process of the LSTM Model

LSTM predicts trading volume through a multi-layer estimation processes sequential time series data through its memory cells. It comprises of three estimation layers: Input layer, LSTM layer (also known as LSTM memory cell), and output layer.

Input Layer: This layer organizes past market returns and trading volume into sequences to enable the model exploring the temporal dependencies over time. Identify and accept sequence of market returns over the defined look back window.

The following diagram describes how the LSTM approach works to examine the bias of overconfidence in the equity market. The model tends to forecast trading volume using past market returns, processed through LSTM layers.

LSTM Hidden Layer (Memory Cell): The core of the estimation lies in the LSTM hidden layer, which combines multiple units (neurons), each cell unit learns by storing and filtering data across time using three gating mechanisms.

- Input gate decides what kind of information flow from the past data should be included in the cell state.
- Forget gate identifies which new information from the past cell to be discarded, and
- Output gate identifies which information from the current cell state is retained as output.

By using this architecture, the model can capture both short-term and long-term dependencies between trading volume and market return to capture nonlinear and delayed effects in investor psychology that are typically overlooked by the traditional econometric methods.

Output Layer: As a result of the learned temporal dependencies between market returns and market trading volume, the output layer predicts trading volume. If the addition of market returns significantly improves the model's predictive performance compared to the volume-only estimation, it confirms empirical evidence that past market returns influence future trading volume. The predictive association reflects investor overconfidence, where investors make trading decisions based on perceived informational advantages from past price movements.

Training Procedure

The motivation of training the model is to minimize the mean squared error (MSE) between the predicted and actual trading volume produced by training data. The training process includes the following model settings:

- LSTM Units: 50
- Rolling window of sequential length: 5 trading days
- Dropout rate: 0.2 to protect model overfitting
- Optimization: Adam (Adaptive Moment Estimation) is a gradient optimization algorithm used to efficiently adjust the learning weights to minimize the prediction errors.
- Epochs: 100 (An epoch is a full phase of dataset used in the LSTM model to gradually learn the patterns in return-volume relationship.
- Training Data: From January 2010-December 2018.
- Loss Function: Refers to Mean Squared Error (MSE) to measure the deviation between trading volume and market return.

The LSTM adjusts its internal weights thorough back propagation over all overlapping sequential windows developed in trained data.

Testing Process

The model predicts trading volume using unseen data over 2019-2021 based on the fixed weights learned from trained data.

The LSTM Evaluation Metric

Model's predictive performance is evaluated based on the **Mean Squared Error (MSE).** The lower value of MSE in the **Restricted Model** relative to the **Baseline Model** (a negative MSE) implies that the inclusion of past market returns improves prediction accuracy of the Augmented model. This finding supports the overconfidence hypothesis indicating that investors base their trading volume decisions on their recent return history.

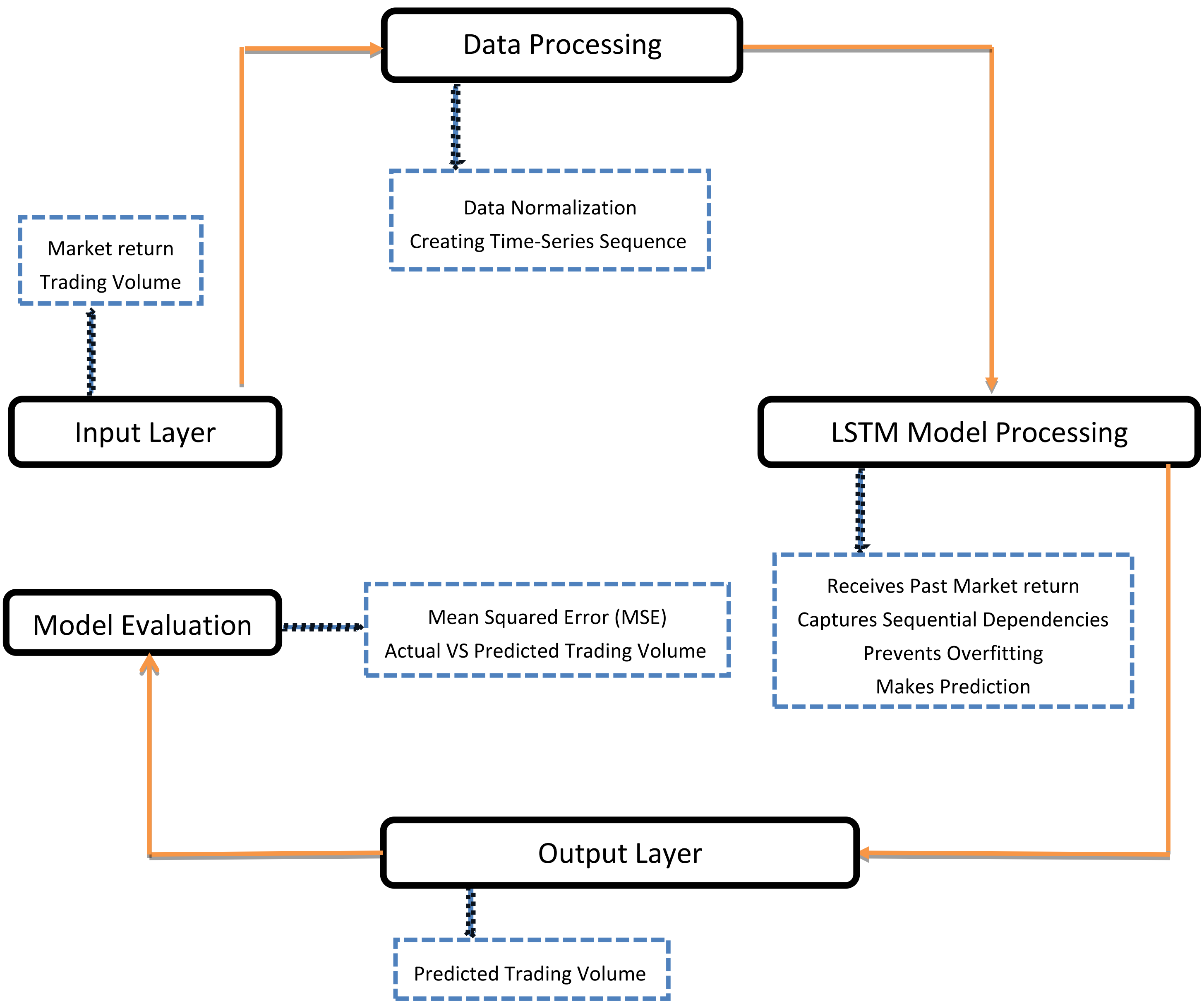


Figure 5.2: Architecture of the LSTM Model

Figure 5.2 describes this multi-layer estimation process to examine the bias of overconfidence in the equity market. The model tends to forecast trading volume using past market returns, processed through LSTM layers.

5.7.3 Determination of Unexpected Market Returns applying the Market Index Model

Existing literature primarily emphasized on the relationship between trading volume and the total market returns to examine overconfidence bias. This thesis shifts focus from the total market returns to the unexpected market returns to precisely measure the existence of overconfidence across diverse market states in the Bangladesh equity market. Investigation of this bias focusing on the unexpected market returns better reflects the surprise or unanticipated component of market returns, which are more likely to trigger investor psychology.

5.7.3.1 Market Index Model Framework

First, it is necessary to distinguish between the expected and unexpected components of aggregate market returns. The component of unexpected return is extracted from the Market Index Model, a prominent and widely used approach followed in securities pricing and event studies (Fama, 1976; Brown & Warner, 1985). The Market Index Model presumes the linear relationship between the return of individual stock and its sensitivity to the broad equity market index, can be modeled as follows:

$$R_t = \alpha + \beta R_{m,t} + \varepsilon_t \qquad (5.16)$$

R_t represents the actual return on each stock at time t.

$R_{m,t}$Represents actual return on a benchmark equally weighted market return at time t

α and β are model parameters estimated through Ordinary Least square (OLS).

ε_tRefers to the residual of the model representing the unexpected or idiosyncratic component of the market returns.

This model is estimated for each stock using historical data over the 2010-2021 to derive the fitted values from the regression analysis. The expected and the unexpected components of the market returns are estimated with the following model specifications:

$$\widehat{R_t} = \alpha + \beta R_{m,t} \qquad (5.17)$$

$$UR_t = R_t - \widehat{R_t} \qquad (5.18)$$

Where, $\widehat{R_t}$ represents the expected return on each stock at time, and UR_t represents the unexpected return for each stock at time t

After estimating both the expected and the unexpected components of each stock return, we determine the equally weighted unexpected aggregate market returns for each day by averaging the unexpected return component of all trading stocks.

5.7.3.2 Rationale for the Unexpected Component of Market Return

Segregation of the unexpected market return is crucial for overconfidence bias analysis because it is presumed that this bias is more likely to prevail in response to unanticipated news or market information. Investors consider these surprises a reflection of their perceived superior knowledge, prompting them to engage in excessive trading activities. This novel framework would enable us to explore whether equity market trading is more strongly influenced by the unexpected market returns than the general market movements.

5.8 Empirical Results

This section systematically provides the empirical findings derived from three distinct and dynamic models such as Vector Autoregressive (VAR) framework, the transfer entropy and advance deep learning long short-Term Memory (LSTM) models across different market states. The analysis also makes efforts for a comprehensive understanding of bias overconfidence by focusing on the asymmetric nature of market environments under general market conditions as well as down and up market returns. This chapter is structured to introduce an orderly flow of overconfidence bias analysis outlining the key results obtained from the VAR framework, focusing on how the model captures the dynamic interrelationships between market returns and trading volumes. Then, the essay explores the findings from the transfer entropy model, emphasizing the causality and directional flow of information transfer between these two variables. Finally, it explains how advanced machine learning models learn long-term behavioral patterns from complex, sequential data to uncover the presence of overconfidence bias. The integration of these approaches may provide a multifaceted perspective on the existence and implications of overconfidence behavioral bias within the context of Bangladesh equity market.

5.8.1 Empirical Results and Discussion from Vector auto regressive (VAR) model

This research intends to empirically examine the overconfidence behavioral bias using aggregate market-wide data in the Bangladesh equity market. Market participants are presumed to exhibit overconfidence in their trading behavior if a causal relationship prevails between lagged market returns and current trading volume. If past values of market returns can more accurately predict the future value of trading volume than the prediction without lagged market returns in the mean square error sense (i.e., $\sigma^2\left(TV_t \middle| \Omega_{t-1}\right) < \sigma^2\left(Y_t \middle| \Omega_{t-1} - R_{mt}\right)$, then it is assumed that market return Granger causes trading volume.

The VAR is the most widely used econometric technique employed in the existing literature to measure the overconfidence fallacy in the equity market (Statman et al., 2006; Metwally & Darwish, 2015; Zia et al., 2017; Mushinada & Veluri, 2018; Shrotryia & Kalra, 2023). The basic VAR framework describes how one endogenous variable can be explained in terms of its own lagged values, the lag values of other endogenous variable and a noise term. This methodology rests upon the lead-lag relationship between past market returns and current trading volume. To investigate robust testing, we perform three VAR causality tests to empirically measure the overconfidence hypothesis.

Table 5.1: The Standard Vector autoregressive (VAR) results

	Overall Market		Bearish Market		Bullish Market	
Variables	TV	R_m	TV	R_m	TV	R_m
TV(t-1)	0.642***	0.029	0.714***	-0.723***	0.621***	-0.060
TV(t-2)	0.191***	-0.360***	0.086***	0.622***	0.241***	-0.116
TV(t-3)	0.121***	0.291***	0.194***	-0.122	0.074***	0.081
R_m(t-1)	-0.004	0.647***	**0.016*****	0.759***	-0.008	0.345***
R_m(t-2)	**0.020*****	0.020	**0.019*****	-0.055***	**0.020*****	0.093***
R_m(t-3)	**0.007*****	-0.002	**0.011*****	0.006	**0.028*****	0.037
CSAD	-.005	-0.239***	-0.003	-0.459***	0.000	0.099***
CSAD(-t-1)	-0.000	0.280***	0.014*	0.560***	-0.020	0.005
CSAD(t-2)	0.009*	-0.052*	0.013*	-0.134***	0.009	-0.055
Volatility	0.000	-0.018***	0.000	-0.013***	0.008	-0.090***
Volatility(t-1)	-0.000	0.006***	0.000***	0.002***	0.008	0.141***
Volatility(t-2)	0.000***	0.002***	0.000	0.003***	0.002	0.036
	Crisis Market		Extended Crisis Market		COVID-19 Market	
Variables	TV	R_m	TV	R_m	TV	R_m
TV(t-1)	0.660***	-3.49***	0.735***	0.209	0.400***	0.092
TV(t-2)	0.112	2.14***	0.084	-1.07	0.410***	-0.330***
TV(t-3)	0.168***	1.00	0.127***	0.834*	0.137***	0.172
R_m(t-1)	**0.040*****	0.576***	-0.002	0.594***	0.026	0.289***
R_m(t-2)	0.008	0.030	**0.029*****	-0.044	-0.000	0.221***
R_m(t-3)	0.004	0.091	**0.006*****	0.010	-0.002	0.172***
CSAD	-0.026	-0.464***	-0.006	-0.633***	-0.000	0.002
CSAD(-t-1)	0.025	0.744***	-0.000	0.583	-0.002	0.002
CSAD(t-2)	-0.012	-0.208	0.014	-0.060***	0.002*	-0.005
Volatility	0.007***	0-.121***	0.000	-0.010***	0.015	0.363***
Volatility(t-1)	-0.001	-0.018	0.000	-0.001	-0.019	-0.093
Volatility(t-2)	0.005	0.092***	0.000***	0.000	-0.002	-0.032

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return. The estimation is performed for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory segregates the overall market into bullish and bearish sectors. A massive crash in January 2011 identified this market as being in crisis. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.
*** Significant at the 1% level
*Significant at the 10% level.
Source: Author's Own Calculation.

Table 5.1 reports on the VAR coefficients for the overall, bearish, bullish, crisis, extended crisis, and COVID-19 markets, respectively. The results are organized with columns for market trading volume and market return and rows for lagged values of both variables in each VAR equation under each market classification. The VAR results designate that, having controlled for exogenous variables, the coefficient of market return is positive and statistically significant at the third lag in the overall and extended crisis markets, advocating that past market returns help investors build their confidence and trade excessively in the subsequent period, which is consistent with the overconfidence hypothesis. The estimated parameters also affirm that a statistically substantial relationship prevails between trading volume and market returns for the first and second lags in the bearish market, for the second and third lags in bullish market, and for the first lag in the crisis market. The findings reinforce the theory of the lead-lag relationship between trading volume and market return, prompting investors' exorbitant trading behavior among investors in both gaining and losing stocks. The VAR results comprehensively evidence the presence of overconfident investors in the Bangladesh equity market. We can proclaim that investors derive confidence from past success in investments, which may result in taking excessive risks and stipulate an inflated sense of overconfidence in future trading decisions. The conclusion is that market participants may rely on biased information when making their trading decisions and therefore overestimating their capabilities to predict the market.

5.8.2 VAR Pairwise Granger Causality Test

The Vector autoregressive (VAR) pair wise Granger causality is an econometric method to measure causal linkages between two variables in a bivariate time series system. Granger causality, developed by Clive Granger in the 1960s, is a statistical approach suggesting that if a variable X Granger causes another variable Y, it is presumed that there is statistically significant information in the past values of X to predict the current value of Y. In the context of VAR framework, the pair wise Granger causality test examines whether past values of one variable in the system have predictive power for another variable after controlling for past values of other variables included in the model.

Table 5.2: VAR Pair wise Granger causality test

Overall Market		
Null Hypothesis	F Statistic	Probability
Market does not Granger cause trade volume	18.29	0.000
Trade volume does not Granger cause market	2.642	
Bearish Market		
Market does not Granger cause trade volume	28.44	0.000
Trade volume does not Granger cause market	2.945	0.052
Bullish Market		
Market does not Granger cause trade volume	9.10	0.000
Trade volume does not Granger cause market	0.891	0.410
Crisis Market		
Market does not Granger cause trade volume	13.14	0.000
Trade volume does not Granger cause market	2.938	0.005
Extended crisis Market		
Market does not Granger cause trade volume	9.049	0.000
Trade volume does not Granger cause market	2.563	.026
COVID-19 Market		
Market does not Granger cause trade volume	0.462	0.708
Trade volume does not Granger cause market	3.624	0.012

Notes: The estimation is carried out for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory is applied to segregate overall market into bullish and bearish. The crisis market was identified because a massive crash happened in January 2011. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.

The null hypothesis is that past values of market return do not possess any potential information for predicting the current value of trade volume beyond what can be explained by the past values of its own and trading volume. The pair wise Granger causality test explores the potential causal relationship between two variables in terms of the overall significance of all the lag values rather than the significance of each individual coefficient of lag values. The empirical results from Table 5.2 evidence that the null hypothesis is rejected at the 1 percent significance level for all markets (overall, bearish, bullish, crisis, and extended crisis) except for COVID-19 period, confirming that market returns contain valuable information to predict future trading volume, suggesting the presence of overconfidence bias among market participants. We argue that investors, influenced by overconfidence, may react excessively to past market information, leading to increased trade volume in the current period.

5.8.3 Toda Yamamoto (1995) Non-Granger Causality Test

Toda Yamamoto (1995) is an alternative test over traditional Granger causality generated with augmented k+dmax based vector autoregressive (VAR) model that follows a chi-square distribution. This causality test is a more robust approach that can accommodate any structural break in time series data. Another feature of Toda Yamamoto model is that it does not require any pre-testing unit root specification. Time series of the concerned variables could be of any order of integration, i.e., I(o), I(1) or I(2). The test statistics of Toda Yamamoto VAR model is formulated on the following conditions:

k+dmax, Where k= Optimal leg length, and dmax= Maximum order of integration

Toda Yamamoto Granger causality test begins with the determination of optimal lag length (k) and maximum order of integration (dmax). Finally, VAR model needs to be estimated with a (k+dmax) order and check for Block Erogeneity Wald test for the desirable direction of causality between two variables in the system.

Table 5.3: VAR Block Exogeneity Wald test

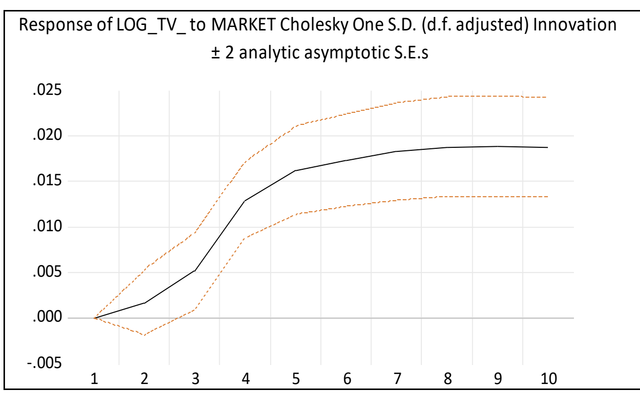
	Overall Market		Bearish Market		Bullish Market	
	Chi-Square	Prob.	Chi-Square	Prob.	Chi-Square	Prob.
R_m	81.57	0.000***	83.02	0.000***	40.43	0.000***
All	81.57	0.000***	83.02	0.000***	40.43	0.000***
	Crisis market		Extended Crisis Market		COVID-19 Market	
	Chi-Square	Prob.	Chi-Square	Prob.	Chi-Square	Prob.
R_m	90.61	0.000***	43.66	0.000***	1.38	0.70
All	90.61	0.000***	43.66	0.000***	1.38	0.70

Notes: The estimation is carried out for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory segregates the overall market into bullish and bearish sectors. A massive crash in January 2011 identified this market as being in crisis By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins. ***Significant at the 1% level.

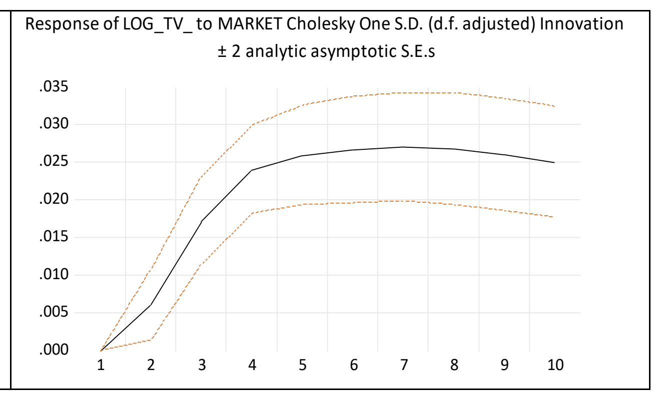
The null hypothesis under the VAR Block Erogeneity Wald test assumes that there is no Granger causality running from market returns to trading volume. The high chi-square value associated with a low probability value indicates strong evidence against the null hypothesis. The empirical findings suggest that lagged market returns have a significant influence on the current trading volume for each market classification except for COVID-19 market. This implies that market participants in the Bangladesh equity market are overconfident and overestimate the precision of their private information, leading to more successive trading on risky stocks because of an underestimation of the risks. The results are the same under the name of variable “All”, which confirms that the test focused on the entire block of variables in the equation, revealing that lagged market returns and lagged trading volume have a statistically significant impact on trading volume.

5.8.4 Impulse response functions (IRFs)

Besides the VAR methodology, we tend to investigate overconfidence bias using impulse response functions (IRFs), which are crucial tools signifying insights into the dynamic relationships between variables in the VAR system subject to a shock to one endogenous variable. IRF examines how a one-time innovation to one of the variables in the VAR framework may impact the current and future values of other variables. IRFs provide not only the dynamic response of market trading volume to market return shocks but also capture how long the impact of shocks persists. This econometric tool examines how an innovation to market return exerts influence on trading volume over subsequent periods, enabling investors to recognize trading patterns consistent with the overconfidence hypothesis.



Overall Market



Bearish Market

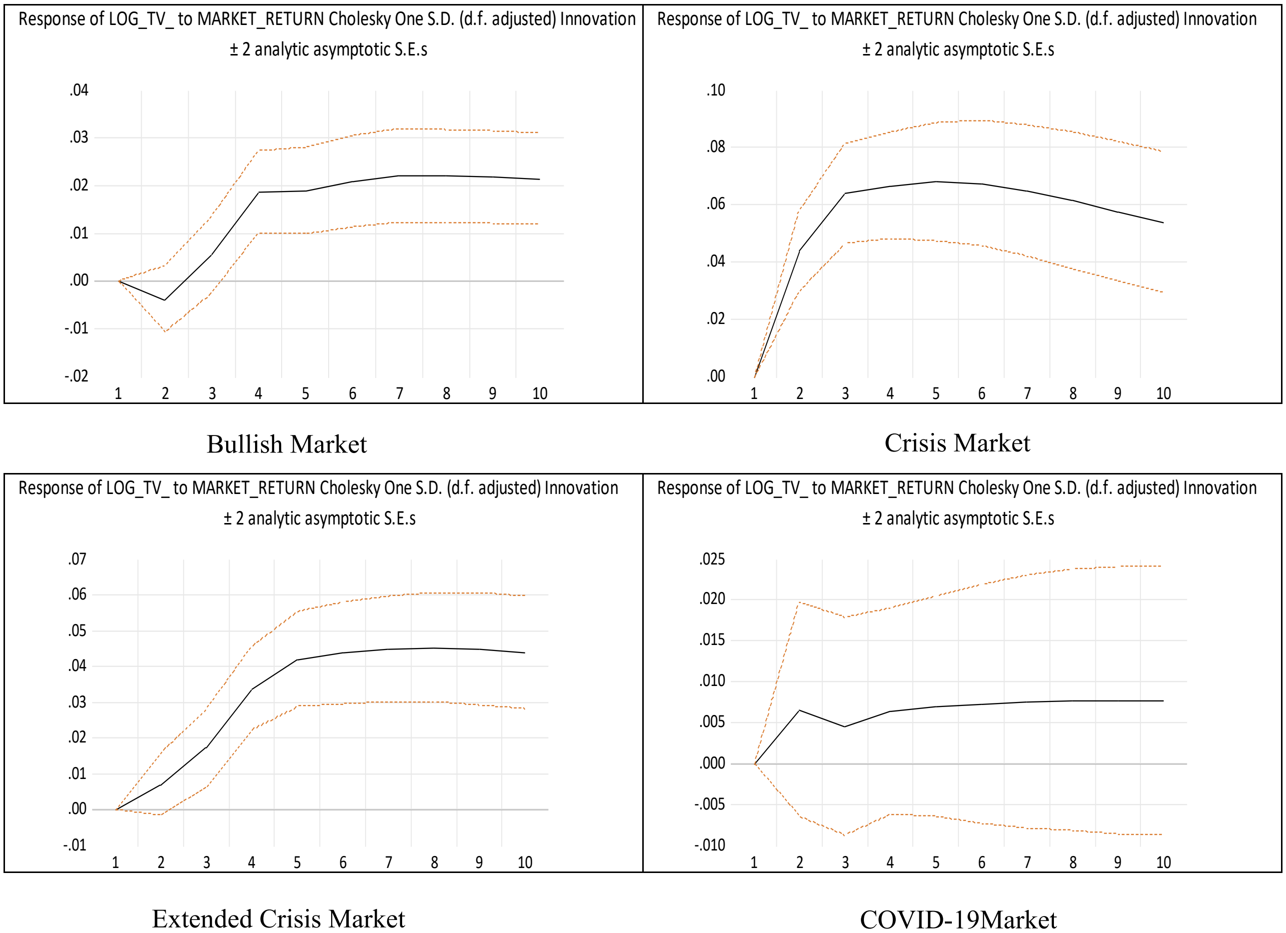


Figure 5.3: Impulse response of trading volume to market returns

The figure depicts the impulse response functions of market trading volume to the aggregate market return for each of the market periods and is estimated for a period of 10 future days. It registers an upward trend overall, bearish, bullish, and extended crisis markets over all future periods. However, the market volume response to market return shocks is positive until period 6 and then continues to decline in the crisis market, and the trend becomes nearly zero beyond period two for COVID-19 market. It is documented that the positive impulse responses are persistent over the future periods for all markets except the crisis and COVID-19 periods. These findings are similar to the earlier results documented in all variations of VAR estimation. It can be inferred that market participants in the Bangladeshi equity market overestimate their capabilities and may react positively to market gains by executing more trade, reinforcing the overconfidence bias.

5.8.5 Asymmetric response of trading volume to market return: Up market

Since we document the presence of overconfidence bias in the Bangladesh equity market, the attention is turned to the asymmetric response of market trading volume to market return across all market segmentations such as entire period, bullish, bearish, crisis, extended crisis, and COVID-19 markets. The phenomenon of asymmetric behaviors may prevail in the equity market in which market participants react differently to positive and negative market movements.

During positive market returns, investors may attribute the gains as a validation of their superior knowledge. This may result in an increased trading volume since they attempt to capitalize on their perceived confident market predictions.

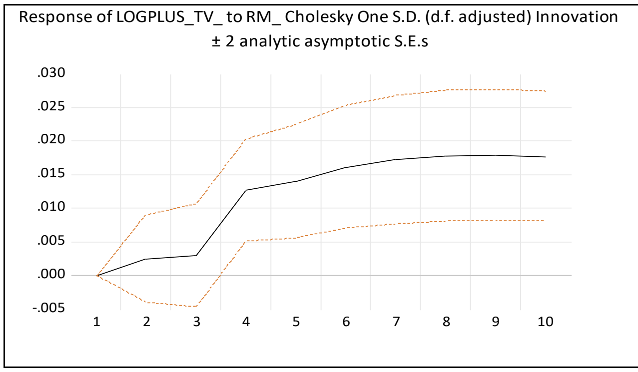
Table 5.4: Basic Vector autoregressive (VAR) results under up market

Parameter	Overall Market	Bearish Market	Bullish Market	Crisis Market	Extended Crisis market	COVID-19 Market
TV(-1)	0.660***	0.707***	0.617***	0.517***	0.877***	0.458***
TV(-2)	0.199***	0.114**	0.264***	0.355***	0.089	0.394***
TV(-3)	-0.003	0.046	0.022	0.033	-0.010	0.068
R_m(-1)	0.005	0.004	0.004	0.008	**0.033*****	.046
R_m(-2)	0.001	**0.048*****	**0.050*****	0.039	0.001	-0.050
R_m(-3)	**0.025*****	0.003	0.013	0.034	0.016	-0.006
CSAD	0.000	0.009	0.007	-0.06	0.005	0.001
CSAD(-1)	0.0002	-0.029	-0.016	-0.014	0.015	-0.001
CSAD(-2)	-0.003	0.024***	-0.022	-0.019	-0.045***	0.001
Volatility	0.000	-0.000	0.002	0.017	0.003	0.003
Volatility(-1)	-0.000	0.000	-0.005	0.004	-0.005	-0.004
Volatility(-2)	0.000	-0.000	-0.006	0.003	0.012***	0.000

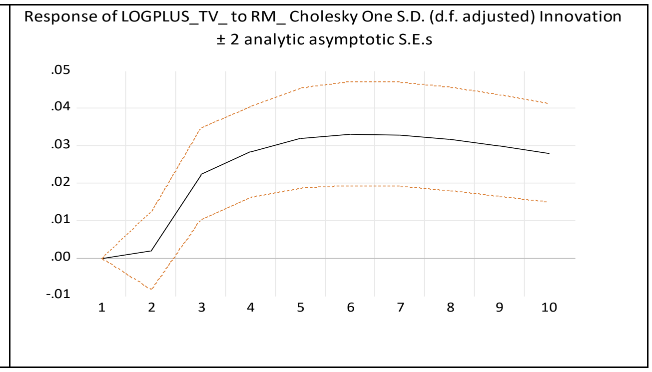
Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return. The estimation is performed for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory segregates the overall market into bullish and bearish sectors. A massive crash in January 2011 identified this market as being in crisis. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.

*** significant at the 1% level
Source: Author's own calculation

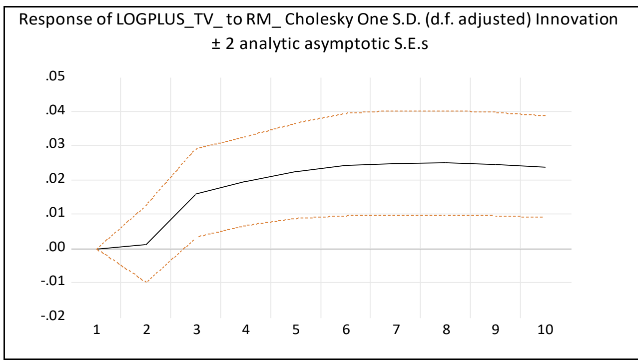
The results from Table 5.4 reveal that the lagged market return exhibits a significant positive effect on trading volume in the entire period, bearish, bullish, and extended crisis markets. This relationship aligns with the theory of overconfidence, which holds that investors overreact to past information and extrapolate their past performance into future expectations, which may lead them to trade more aggressively. However, overconfidence does not hold in the crisis and COVID-19 periods and suggests that during crisis times other factors might overshadow the predictive power of past returns on trading volume. The finding is also corroborated by the following impulse response functions.



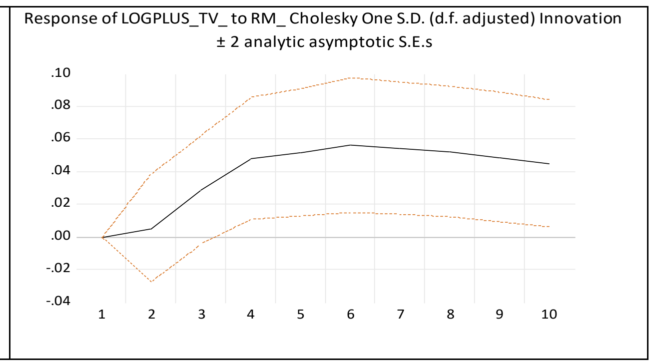
Overall Market



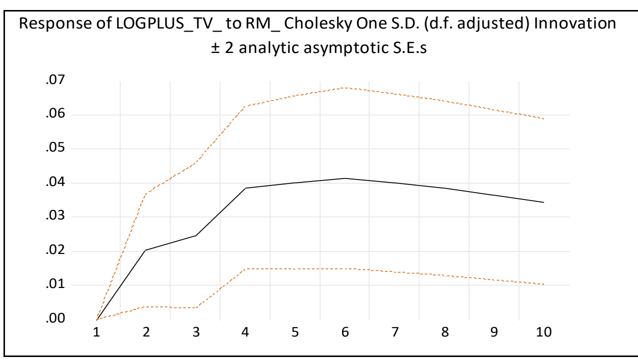
Bearish Market



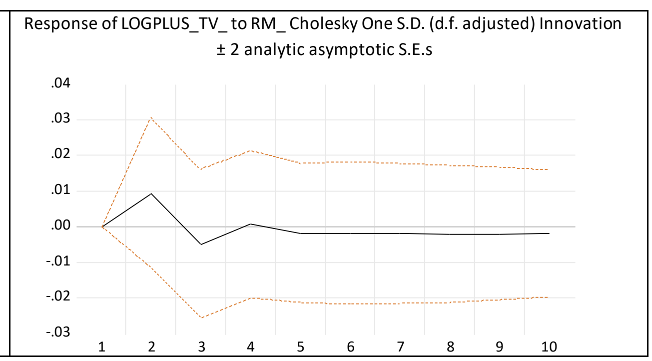
Bullish Market



Crisis Market



Extended Crisis Market



COVID-19 Market

Figure 5.4: Impulse response of trading volume to market returns under up markets

Table 5.5: VAR pair wise Granger causality test under up market

Null Hypothesis	F Statistic	Probability
Overall Market		
Market does not Granger cause trade volume	3.39	0.0025
Trade volume does not Granger cause market	0.644	0.694
Bearish Market		
Market does not Granger cause trade volume	9.82	0.000
Trade volume does not Granger cause market	21.08	0.000
Bullish Market		
Market does not Granger cause trade volume	4.42	0.000
Trade volume does not Granger cause market	1.47	0.221
Crisis Market		
Market does not Granger cause trade volume	2.79	0.044
Trade volume does not Granger cause market	14.86	0.000
Extended crisis Market		
Market does not Granger cause trade volume	3.97	0.000
Trade volume does not Granger cause market	0.986	0.399
COVID-19 Market		
Market does not Granger cause trade volume	0.573	0.632
Trade volume does not Granger cause market	3.74	0.011

Notes: The estimation is carried out for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory is applied to segregate overall market into bullish and bearish. The crisis market was identified because a massive crash happened in January 2011. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.

Table 5.6: VAR Block Exogeneity Wald test under market

	Overall Market		Bearish Market		Bullish Market	
	Chi-Square	Prob.	Chi-Square	Prob.	Chi-Square	Prob.
R_m	20.39***	0.002	29.47***	0.000	13.28***	0.000
All	20.39***	0.002	29.47***	0.000	13.28***	0.000
	Crisis market		Extended Crisis Market		COVID-19 Market	
	Chi-Square	Prob.	Chi-Square	Prob.	Chi-Square	Prob.
R_m	8.37**	0.039	11.92***	0.007	1.72	0.632
All	8.37**	0.039	11.92***	0.007	1.72	0.632

Notes: The estimation is performed for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory is applied to segregate overall market into bullish and bearish. A massive crash in January 2011 identified this market as being in crisis. Extended market captures how crisis prolongs just extending crisis period six-month before and after the event. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.
***Significant at the 1% level

Table 5.5 and 5.6 testimony the findings from both the paired Granger causality and VAR Block Exogeneity Wald tests. We find that the results are the same as those documented earlier for the basic VAR model, with the exception that the crisis market shows evidence of the overconfidence bias. This is also confirmed by the impulse response functions presented in Figure 5.4.

5.8.6 Asymmetric response of trading volume to market return: Down market

This part focuses on the relationship between market return and trading volume under down market conditions. The asymmetric response of market participants emphasizes the need to explore how negative returns can evoke their emotional attitudes across various market states. We examine whether the hypothesized relationship between market return and trading volume holds true in down market movements, which may signify the nature of investors excessive trading activity within the framework of market classifications including overall, bearish, bullish, crisis, extended crisis, and COVID-19.

Table 5.7: Basic Vector autoregressive (VAR) results under down market

Parameter	Overall Market	Bearish Market	Bullish Market	Crisis Market	Extended Crisis market	COVID-19 Market
TV(-1)	0.748***	0.748***	0.753***	0.737***	0.726***	0.852***
TV(-2)	0.031	0.031	0.118***	0.083	0.088	-0.104
TV(-3)	0.111***	0.111***	0.050	0.143	0.122	0.237***
R_m(-1)	**0.006*** **	0.008	0.003	**0.029*** **	**0.007*** **	0.036
R_m(-2)	-0.004	0.005	0.001	-0.015	-0.004	-0.002
R_m(-3)	**0.005** **	-0.000	**0.035** **	-0.010	0.005	**0.074*** **
CSAD	-0.007	0.009	-0.028	0.015	-0.014	0.000
CSAD(-1)	0.004	0.003	0.015	-0.022	0.019	-0.002
CSAD(-2)	0.008	-0.013	-0.007	-0.003	-0.017	0.002
Volatility	0.000	-0.000	0.006	0.000	0.004	-0.002
Volatility(-1)	-0.000	-0.000	-0.012	0.003	-0.000	-0.013
Volatility(-2)	-0.000	0.000	0.008	-0.009**	0.003	0.050***

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return. The estimation is performed for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory segregates the overall market into bullish and bearish sectors. A massive crash in January 2011 identified this market as being in crisis. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.
*** significant at the 1% level
**Significant at the 5% level.
Source: Author's own calculation.

The results from Table 5.7 uncover that the hypothesis of aggregate market return can significantly influence trading volume for the overall, crisis, extended crisis, and COVID-19 markets. This robust finding of hypothesis supported with significance at the 1 percent level denotes a persistent and pronounced effect of market return on trading volume presumably reflect the intensified investor response and cognitive biases throughout these market scenarios. On the other hand, a relatively lower level of significance as observed at the 5 percent level in bullish market indicates a less pronounced asymmetric response of investors, which may possibly be attributed to their increased optimism of reversing the aggregate market movements. Our findings reveal that the overconfidence hypothesis was not found significant in either normal market conditions or up market movement during the COVID-19 pandemic. However, it showed statistical significance under down market situation in the COVID-19 market phase. This suggests that negative market trends may exacerbate the emotional attitudes of market participants during crisis events like pandemic, impacting the market trading volume more prominently. In a crisis time, investors may overestimate their knowledge to predict market reversals believing that they can capitalize on mispriced securities to recover losses, therefore fueling the aggregate trading activity.

The findings of VAR framework under down market conditions described above are further corroborated by the impulse response functions (IRFs), which graphically demonstrates the dynamic relationship that whether the influence of market return can persist over the specific future time. These IRFs illustrations reinforce the evidence of asymmetric behavioral nature of investors trading activity across different markets states during negative market movements.

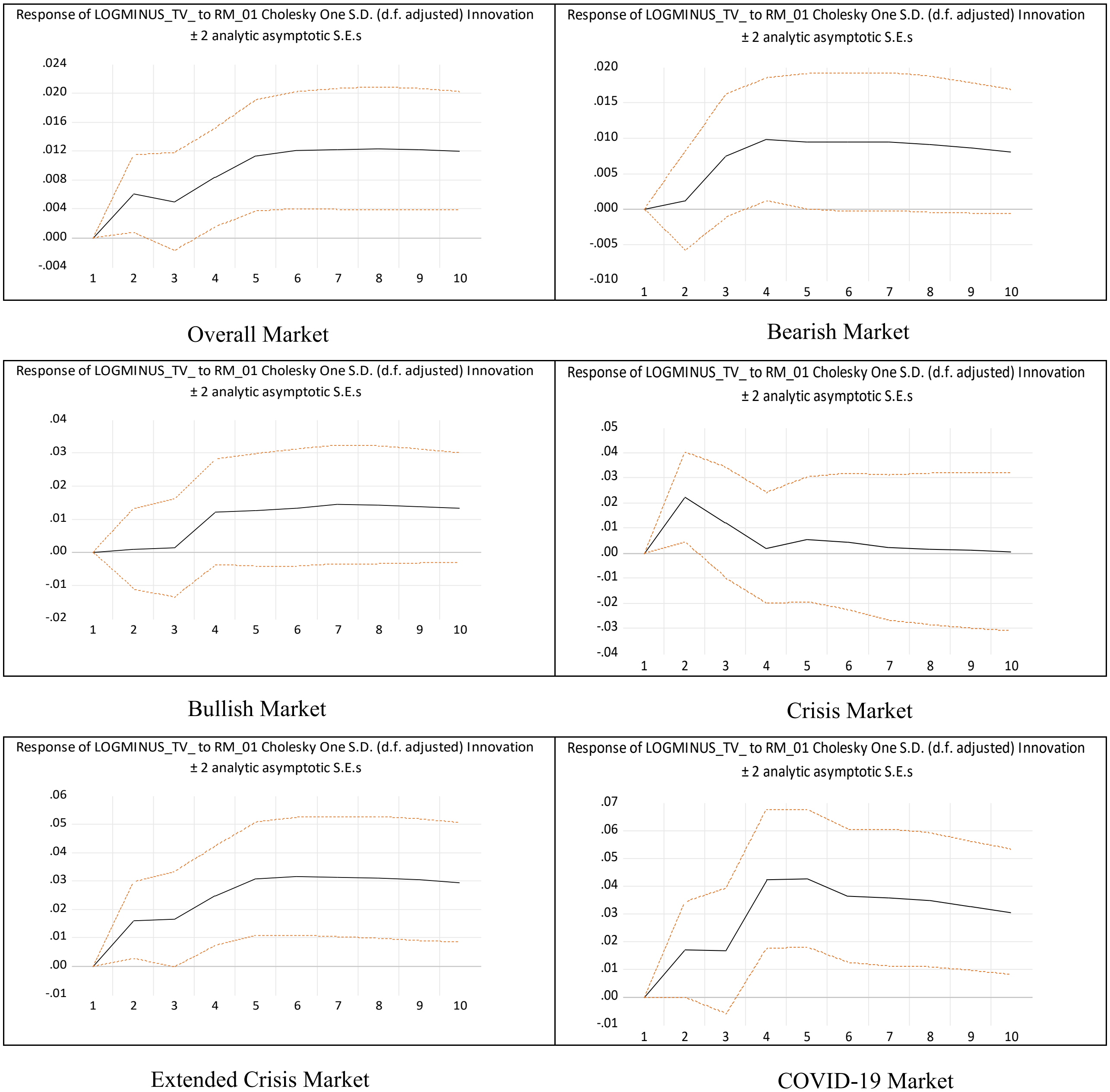


Figure 5.5: Impulse response of trading volume to market returns under down markets

5.8.7 Examining the relationship between unexpected market returns and market trading volume under VAR framework

This section attempts to examine overconfidence hypothesis in the Bangladesh equity market by focusing on the relationship between unexpected market returns and trading volumes. We employed the market index model to develop unexpected returns, which enabled us to separate deviations in equity returns that could not be explained by the general market movements. These individual unexpected equity returns for each day were then aggregated to determine the overall market unexpected returns. The motivation is to examine whether the fluctuations in unexpected market returns can be related to increased trading activity, which may accurately signal overconfidence bias among equity market investors.

Table 5.8: The Standard Vector autoregressive (VAR) results with unexpected returns

	Overall		Bearish		Bullish	
Variables	TV	UnR_m	TV	UnR_m	TV	UnR_m
TV(t-1)	0.653***	-0.038	0.700***	-0.286***	0.775***	-0.018
TV(t-2)	0.183***	-0.102	0.057	0.155	0.046	-0.211
TV(t-3)	0.116***	0.164***	0.169***	-0.002	0.114***	0.288***
R_m(t-1)	-0.002	0.208***	**0.033*****	0.353***	0.005	0.139***
R_m(t-2)	**0.026*****	0.153***	**0.039*****	0.196***	**0.028*****	0.069***
R_m(t-3)	**0.011*****	0.089***	**0.015*****	-0.050***	**0.041*****	0.079***
CSAD	-0.005	0.098***	-0.007	0.049***	-0.008	0.470***
CSAD(-t-1)	0.004	-0.009	0.011	-0.123***	0.006	-0.098***
CSAD(t-2)	0.000	-0.032	0.011	0.121***	-0.000	-0.238***
Volatility	-0.000	-0.001***	-0.000	0.004***	0.008	-0.099***
Volatility(t-1)	-0.000	-0.001***	-0.000	-0.000	-0.000	0.055***
Volatility(t-2)	-0.000***	0.000	-0.000***	-0.003***	0.000	0.073***
	Crisis Market		Extended Crisis		COVID-19 Market	
Variables	TV	UnR_m	TV	UnR_m	TV	UnR_m
TV(t-1)	0.686***	-1.13***	0.764***	0.049	0.425***	0.167
TV(t-2)	0.043	0.327	0.054	-0.304	0.409***	-0.203
TV(t-3)	0.184***	0.653***	0.124***	0.297	0.109***	0.086
R_m(t-1)	**0.074*****	0.573***	0.005	0.584***	-0.034**	-0.291***
R_m(t-2)	0.020	0.073	**0.051*****	-0.052	0.019	0.008
R_m(t-3)	0.013	0.088	0.007	0.031	0.013	0.097*
CSAD	-0.014	0.121	-0.007	0.150***	0.000	0.009***
CSAD(-t-1)	0.006	0.204***	0.014	-0.047	-0.003**	-0.026***
CSAD(t-2)	-0.008	-0.162***	-0.012	-0.082***	0.002	0.011
Volatility	0.007***	-0.045***	-0.000	0.002***	0.011	0.027
Volatility(t-1)	-0.003	-0.037***	-0.000	-0.002***	-0.011	0.079
Volatility(t-2)	0.005	0.022	-0.000	0.002***	-0.001	0.134**

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return. The estimation is performed for the overall market, bearish, bullish, crisis (04/07/2010-30/06/2011), extended crisis (04/01/2010-29/12/2011), and COVID-19 markets (08/03/2020-31/12/2021). Dow Theory segregates the overall market into bullish and bearish sectors. A massive crash in January 2011 identified this market as being in crisis. By extending the crisis period six months before and after the event, extended markets capture how crises prolong. When the first pandemic patient is identified in Bangladesh, the COVID-19 period begins.

*** Significant at the 1% level

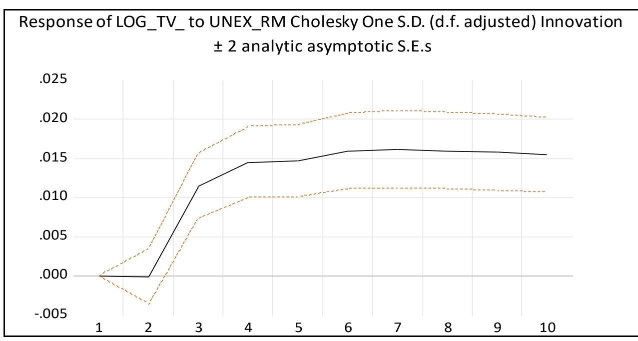
**Significant at the 5% level.

*Significant at the 10% level.

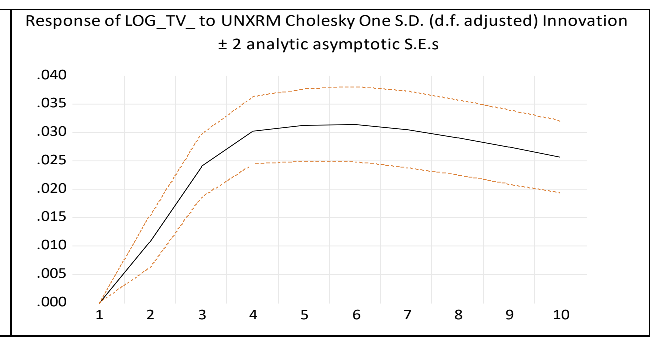
Source: Author's Own Calculation.

Table 5.8 sheds light on whether unexpected components of market returns can significantly influence market trading activity, which indicates the presence of overconfidence bias. In the overall market, the statistical significance of lag two and three of unexpected market returns at the 1 percent level reveals that past market shocks can consistently drive market trading volumes. The consistent significant lag effects of unexpected market return in both bearish and bullish markets suggest that overconfidence may stem from psychological behavior of investors, such as optimism in bullish market and loss aversion or anticipated market reversals in bearish market. The presence of significant first lag of unexpected market returns in crisis market and the second lag in extended crisis market reflects that overconfidence is still prevalent during heightened market uncertainty. However, when a crisis persists for a long time, investors may become less reactive in the short period but do not refrain from biased trading, indicating that their decisions are driven by cognitive biases. Finally, the absence of overconfidence bias during the COVID-19 market highlights that investors may have been less reluctant to take actions on perceived predictions during severe risky environment, leading them to initiate more restrained trading behavior.

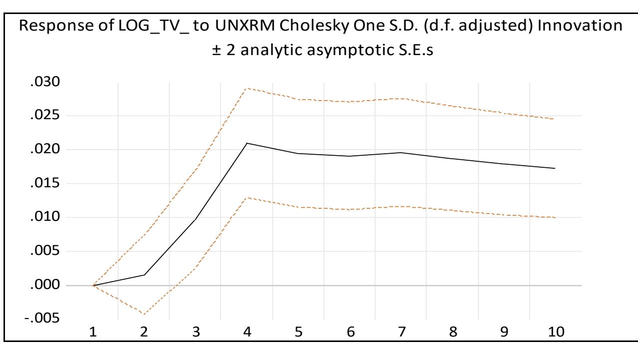
The robust findings provide novel insights into the manifestation of overconfidence bias in the Bangladesh equity market across different market states by focusing on unexpected component of market returns. This suggests that investors have the tendency to overestimate their capabilities to predict aggregate market trends, leading to increased trading activities.



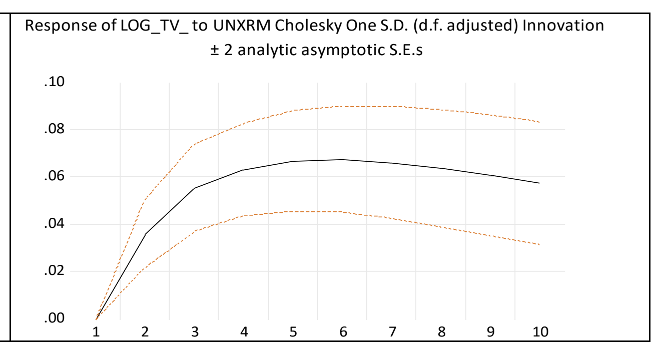
Overall Market



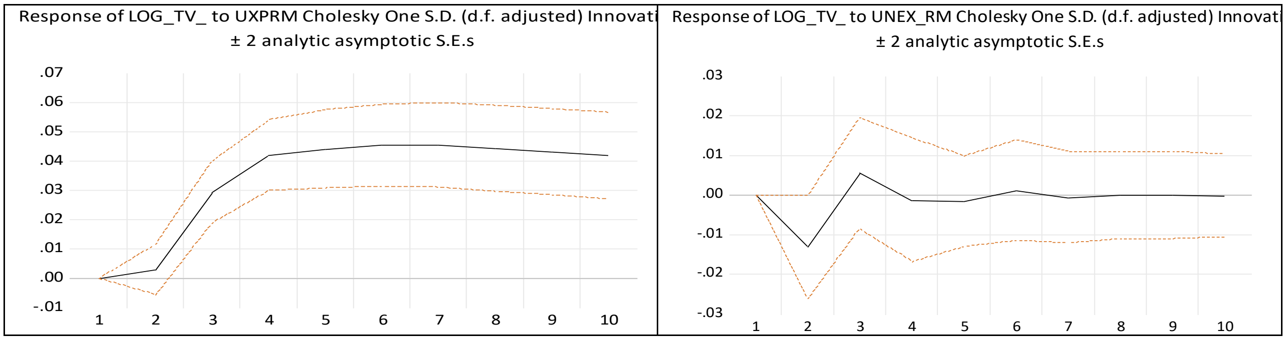
Bearish Market



Bullish Market



Crisis Market



Extended Crisis Market   Covid-19 Market

Figure 5.6: Impulse response of trading volume to unexpected market returns

The impulse response functions (IRFs) measure how one variable dynamically responds to a one-unit shock in another variable within a VAR framework. The black line represents how market trading volume responds to a shock in unexpected market return. It clearly shows an initial positive response after a shock and then the response gradually decays over time, indicating how long the reaction of investors may persist before it returns to equilibrium. The orange dashed lines do not cross zero in all market classifications except COVID-19 period, supporting our overconfidence hypothesis that unexpected market return can predict trading activity in the Bangladesh equity market. These IRFs findings are aligning with the VAR results that lagged aggregate total return can influence market trading behavior.

5.8.8 Empirical Results and Discussion from Transfer Entropy Model

5.8.8.1 Examining the relationship between market return and trading volume using Transfer Entropy model

Transfer entropy intends to estimate the direction of information flow shared between two time series variables. The higher transfer entropy value confirms a stronger amount of information flow meaning that the predictive information flow from one variable to another is quantitatively stronger.

Table 5.8 Shannon Transfer Entropy results for the Overall Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \rightarrow TV}$	0.0058	0.0030	0.0012	0.010**
$TE_{TV \rightarrow R_m}$	0.0145	0.0115	0.0013	0.002***

Bootstranpped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \rightarrow TV}$	0.0004	0.0018	0.0026	0.0034	0.0076
$TE_{TV \rightarrow R_m}$	0.0005	0.0020	0.0026	0.0036	0.0085

Notes: $TE_{R_m \rightarrow TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \rightarrow R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5.9 reports the transfer entropy results for the overall equity market period. The coefficient of 0.0058 is significant at the 5 percent level, suggesting a weaker information transfer from market return to market trading volume, whereas the transfer entropy coefficient of 0.0145 is also significant at the 1 percent level indicating a stronger information transfer from trading volume to market return. Effective transfer entropy is a refined adjusted value of transfer entropy used to measure the significance of causality direction after controlling for any kind of bias effect or redundancy in information transfer estimation. The statistically significant higher coefficient of effective transfer entropy confirms a weaker net flow from market return to market trading volume.

The bootstrapped transfer entropy provides a robust estimate by focusing on the distribution of transfer entropy values through random simulations done over 300 replications. The range of transfer entropies across quantiles provides an intuition of how the direction of estimated information transfer between two variables can be comparable in magnitude. The bootstrapped transfer entropy values show consistently higher estimations across replicated samples indicating that market return has a lower impact on market trading volume rather than the other direction, reinforcing its less strong causal effect. We conclude that although the findings affirm a bidirectional transfer of information flow between these two market variables, the causality direction from market return to trading volume is less significantly pronounced, weakly supporting the overconfidence hypothesis in the Bangladesh equity market.

Table 5.10: Trend-Driven Equity Market Phases

Panel A: Shannon Transfer Entropy results for Bearish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0026	0.0000	0.0017	0.8200	
$TE_{TV \to R_m}$	0.0137	0.0090	0.0019	0.0000***	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0003	0.0030	0.0041	0.0053	0.0093
$TE_{TV \to R_m}$	0.0012	0.0028	0.0041	0.0055	0.0124
Panel B: Shannon Transfer Entropy results for Bullish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
.$TE_{R_m \to TV}$	0.0176	0.0114	0.0023	0.0000***	
$TE_{R_m \to TV}$	0.0180	0.0107	0.0027	0.0300**	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0017	0.0051	0.0066	0.0086	0.0190
$TE_{R_m \to TV}$	0.0016	0.0043	0.0059	0.0075	0.0130

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5.10 presents the results for the trend-driven, bearish and bullish markets to uncover significant differences in information transfer patterns. Panel A reveals the absence of statistically significant information transfer from market return to trading volume for bearish market. However, Panel B shows the transfer entropy coefficient is statistically significant at the 1 percent level in bullish market, suggesting that past values of market return exert a more pronounced impact on the future state of trading volume. The bootstrapped transfer entropy quantiles further reinforce the robustness of this finding exhibiting a slightly stronger flow of information from market return to trading volume. The results indicate that the overconfidence bias may be more prevalent in bullish market phase of Bangladesh equity market, attributing to the intensified investor optimism and their overreaction to the uptrend market signal.

The findings convey that overconfidence bias manifests distinctly in bullish market phase, exhibiting a stronger directional causality from market return to trading volume, which is more consistent with investor excessive trading behavior driven by positive market sentiment. This aligns with the theory of behavioral finance that investors may overestimate their knowledge to predict market movements, contributing to increased market trading activity.

Table 5.11: Crisis-Driven Equity Market Phases

Panel A: Shannon Transfer Entropy results for Crisis Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0128	0.0000	0.0087	0.5133
$TE_{TV \to R_m}$	0.0097	0.0000	0.0083	0.5433

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0020	0.0092	0.0130	0.0189	0.0546
$TE_{TV \to R_m}$	0.0028	0.0113	0.0154	0.0215	0.0520

Panel B: Shannon Transfer Entropy results for Extended Crisis Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0075	0.0000	0.0040	0.7200
$TE_{R_m \to TV}$	0.0193	0.0000	0.0048	0.5000

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0028	0.0072	0.0095	0.0121	0.0252
$TE_{R_m \to TV}$	0.0025	0.0077	0.0102	0.0135	0.0267

Panel C: Shannon Transfer Entropy results for COVID-19 Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0067	0.0000	0.0068	0.8067
$TE_{TV \to R_m}$	0.0173	0.0031	0.0053	0.1700

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0016	0.0073	0.0102	0.0156	0.0408
$TE_{R_m \to TV}$	0.0028	0.0088	0.0111	0.0156	0.0393

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

The findings from Table 5.11 show that the transfer entropy analysis revealed no significant coefficient for crisis, extended, and COVID-19 markets. This suggests that overconfidence hypothesis, in which market return can significantly influence trading volume, was not confirmed in these market states. The absence of this significant information transfer conveys that market participants may have the tendency to shift their focus from past market behavior to other external issues (macroeconomic shocks, political tensions, global events etc.), which dilutes the influence of historical market return on market trading activity.

We may conclude that overconfidence hypothesis is significantly evident in the entire market as well as trend-driven market phases, suggesting that investors in the Bangladesh equity market may respond to past market returns and subsequently make more trading decisions potentially influenced by optimism in bull market and pessimism in bear market. This robust finding across this market states may align with the proposition that investors' decision-making process are prominently influenced by their cognitive biases.

5.8.8.2 Examining asymmetric response of market return to trading volume: Up market conditions

This section begins with the transfer entropy analysis to examine the asymmetric impact of overconfidence hypothesis under up and down-market returns conditions across various market states including overall, bearish, bullish, crisis, extended crisis, and COVID-19 markets.

Table 5.12: Trend-Driven Equity Market Phases under Up Market

Panel A: Transfer Entropy results for Overall Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0083	0.0030	0.0020	0.1500	
$TE_{TV \to R_m}$	0.0074	0.0025	0.0022	0.1133	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0008	0.0031	0.0043	0.0056	0.0137
$TE_{TV \to R_m}$	0.0012	0.0037	0.0050	0.0067	0.0147
Panel B: Transfer Entropy results for Bearish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0110	0.0120	0.0043	0.2133	
$TE_{R_m \to TV}$	0.0178	0.0022	0.0042	0.0367	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0027	0.0067	0.0089	0.0119	0.0291
$TE_{R_m \to TV}$	0.0016	0.0070	0.0090	0.0120	0.0257
Panel C: Transfer Entropy results for Bullish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0125	0.0158	0.0043	0.2167	
$TE_{TV \to R_m}$	0.0132	0.0004	0.0042	0.0900	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0028	0.0077	0.0105	0.0128	0.0261
$TE_{R_m \to TV}$	0.0018	0.0066	0.0089	0.0114	0.0257

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

In a positive equity market environment, investors are typically optimistic about the future and more likely to trade frequently, which is usually driven by the belief that the market will continue to gain value in the long run.

The findings from the transfer entropy analysis in Table 5.12 reveal no statistically significant coefficient across trend-driven markets, confirming the absence of directional information flows from market return to market trading volume during periods of rising market returns. On the other hand, Table 13 reports that the transfer entropy coefficients in the crisis-driven market states were also not significant, suggesting that market return does not have significant influence on trading volume during periods of up market trend. This lack of significant transfer entropy coefficients during up-market returns across all market states clearly that positive market movements may quickly accommodate information and may not trigger any behavioral attitudes among investors strong enough to capture the causality direction from market return to trading volume.

Table 5.13: Crisis-Driven Equity Market Phases Up Market

Panel A: Transfer Entropy results for Crisis Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0147	0.0000	0.0086	0.5200
$TE_{TV \to R_m}$	0.0143	0.0000	0.0090	0.4833

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0000	0.0087	0.0181	0.0287	0.0998
$TE_{TV \to R_m}$	0.0011	0.0187	0.0164	0.0287	0.1425

Panel B: Transfer Entropy results for Extended Crisis Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0088	0.0000	0.0093	0.8233
$TE_{R_m \to TV}$	0.0111	0.0000	0.0079	0.7633

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0019	0.0096	0.0133	0.0194	0.0633
$TE_{R_m \to TV}$	0.0032	0.0114	0.0142	0.0195	0.0582

Panel C: Transfer Entropy results for COVID-19 Market

Direction	TE Coefficient	ETE Coefficient	Standard error	P-value
$TE_{R_m \to TV}$	0.0147	0.0000	0.0097	0.5067
$TE_{TV \to R_m}$	0.0143	0.0000	0.0085	0.5133

Bootstrapped Transfer entropy Quantiles (300 replications)

Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0025	0.0098	0.0149	0.0215	0.0626
$TE_{R_m \to TV}$	0.0046	0.0110	0.0145	0.0203	0.0563

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level. *** Significant at the 1% level.

5.8.8.3 Examining asymmetrical response of market return to trading volume: Down-market conditions

In contrast to positive market returns, investors often exhibit heightened anxiety and risk aversion. The study also attempts to explore the robustness of transfer entropy model to investigate whether information flows from market return to trading volume persists or changes during down market returns across a variety market state.

Table 5.14: Trend-Driven Equity Market Phases Down Market

Panel A: Shannon Transfer Entropy results for Overall Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0118***	0.0178	0.0021	0.0000	
$TE_{TV \to R_m}$	0.0408**	0.0040	0.0020	0.0467	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0008	0.0029	0.0041	0.0055	0.0123
$TE_{TV \to R_m}$	0.0011	0.0031	0.0042	0.0057	0.0133
Panel B: Shannon Transfer Entropy results for Bearish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0090	0.0019	0.0028	0.1300	
$TE_{R_m \to TV}$	0.0159**	0.0102	0.0023	0.0533	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0010	0.0041	0.0056	0.0075	0.0169
$TE_{R_m \to TV}$	0.0015	0.0051	0.0064	0.0079	0.0141
Panel C: Shannon Transfer Entropy results for Bullish Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0111	0.0000	0.0047	0.5200	
$TE_{TV \to R_m}$	0.0554**	0.0436	0.0058	0.0520	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0022	0.0086	0.0108	0.0142	0.0353
$TE_{R_m \to TV}$	0.0006	0.0071	0.0103	0.0138	0.0377

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5.14 and Table 5.15 represent that the transfer entropy results across all market states during periods of negative market returns. This result indicates that there is a strong information transfer from market return to trading volume only for overall market, supporting the overconfidence hypothesis where investors may overreact to perceived mispricing or market signals during negative market movements. In contrast, the transfer entropy coefficient from market return to trading volume is not significant for any of the other market states during periods of down-market returns. The absence of this insignificant coefficient during negative market days may neutralize investors' trading strategies and suppress their overestimation capabilities highlighting the effects of heightened uncertainty and external shocks on their psychological behavior in these market states.

Table 5.15: Crisis-Driven Equity Market Phases Down Market					
Panel A: Transfer Entropy results for Crisis Market					
Directon	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0199	0.0000	0.0134	0.5200	
$TE_{TV \to R_m}$	0.0199	0.0000	0.0152	0.3567	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0023	0.0144	0.0205	0.0295	0.0821
$TE_{TV \to R_m}$	0.0043	0.0120	0.0169	0.0243	0.1315
Panel B: Transfer Entropy results for Extended Crisis Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0201	0.0024	0.0076	0.2333	
$TE_{R_m \to TV}$	0.0169	0.0015	0.0069	0.2767	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0049	0.0103	0.0144	0.0193	0.0634
$TE_{R_m \to TV}$	0.0019	0.0092	0.0130	0.0174	0.0514
Panel C: Transfer Entropy results for COVID-19 Market					
Direction	TE Coefficient	ETE Coefficient	Standard error	P-value	
$TE_{R_m \to TV}$	0.0226	0.0035	0.0112	0.2400	
$TE_{TV \to R_m}$	0.0144	0.0000	0.0079	0.5133	
Bootstrapped Transfer entropy Quantiles (300 replications)					
Direction	0%	25%	50%	75%	100%
$TE_{R_m \to TV}$	0.0008	0.0076	0.0147	0.0220	0.0654
$TE_{R_m \to TV}$	0.0057	0.0123	0.0146	0.0182	0.0649

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

5.8.8.4 Examining the relationship between unexpected market returns and market trading volume using Transfer Entropy Model: Under Normal Market Conditions

The study provides a new perspective in the literature of overconfidence bias by distinguishing the total equity market returns into expected and unexpected components, with later being examined to explore this behavioral bias. Unlike existing literature, overconfidence bias is investigated applying an innovative transfer entropy approach to assess this bias, highlighting the relationship between unexpected market returns and trading volume.

Table 5.16: Results of Transfer Entropy model with unexpected market returns							
Overall Market				Bearish Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0130***	0.0099	0.000	$TE_{R_m \to TV}$	0.0070	0.0026*	0.080

$TE_{TV \rightarrow R_m}$	0.0069***	0.0040	0.000	$TE_{TV \rightarrow R_m}$	0.0115	0.0056***	0.000
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \rightarrow TV}$	0.0025	0.0032	0.0042	$TE_{R_m \rightarrow TV}$	0.0043	0.0054	0.0067
$TE_{TV \rightarrow R_m}$	0.0018	0.0025	0.0034	$TE_{TV \rightarrow R_m}$	0.0030	0.0042	0.0053
Bullish Market				Crisis Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \rightarrow TV}$	0.0102**	0.0307	0.050	$TE_{R_m \rightarrow TV}$	0.0159	0.000	0.443
$TE_{TV \rightarrow R_m}$	0.0281***	0.0204	0.000	$TE_{TV \rightarrow R_m}$	0.0188	0.000	0.3133
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \rightarrow TV}$	0.0045	0.0060	0.0077	$TE_{R_m \rightarrow TV}$	0.0097	0.0147	0.0208
$TE_{TV \rightarrow R_m}$	0.0055	0.0069	0.0087	$TE_{TV \rightarrow R_m}$	0.1010	0.0146	0.0206
Extended Market				COVID-19 Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \rightarrow TV}$	0.0117	0.000	0.410	$TE_{R_m \rightarrow TV}$	0.0205	0.0079**	0.053
$TE_{TV \rightarrow R_m}$	0.0047	0.000	0.960	$TE_{TV \rightarrow R_m}$	0.0265	0.0130**	0.033
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \rightarrow TV}$	0.0080	0.0105	0.0134	$TE_{R_m \rightarrow TV}$	0.0068	0.0113	0.0141
$TE_{TV \rightarrow R_m}$	0.0075	0.0098	0.0130	$TE_{TV \rightarrow R_m}$	0.0095	0.1133	0.0384

Notes: $TE_{R_m \rightarrow TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \rightarrow R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

The unexpected market return can be identified as a new phenomenon to examine overconfidence in behavioral finance literature since it captures the variations in market return that cannot be measured by market information, reflecting the element of surprises in overall market movements. Table 5.16 provides the results of transfer entropy on the relationship between unexpected market returns and trading volume across various market states. The statistically significant unexpected return in the overall market suggests a robust flow of information transferring from unexpected return to trading volume. Overconfidence bias seems to appear in the Bangladesh equity market and may cause investors to attribute unexpected returns to their perceived superior knowledge and belief, leading to increased trading activities. A weaker presence of overconfidence bias was also found in the bullish market, as unexpected return is significant at the 5 percent level, reinforcing investors' belief in the trading capabilities in rising market movements. Overconfidence bias was not present in bearish, crisis, extended crisis, and COVID-19, indicating that investors become more cautious in these market states and their trading behavior is not influenced by psychological factors. We may conclude that overconfident bias being more prominent in normal and optimistic equity market environments.

5.8.8.5 Examining the asymmetrical relationship between unexpected market returns and market trading volume using Transfer Entropy Model: Under Up Market Condition

Table 5.17 reports the transfer entropy results for examining the relationship between unexpected market returns and trading volume during the periods of up-market movements and found that unexpected market returns do not significantly influence trading volume in any of these market states. The overconfidence-driven trading behavior of investors is not exhibited during up-market returns condition, suggesting that positive returns capture their optimism, and therefore, reducing the impact of unexpected market returns on trading activities. In a positive market return, trading behavior of investors may be driven by momentum rather than their capabilities to overestimate the market movements.

Table 5.17: Transfer Entropy results with unexpected market returns under Up Market

Overall Market				Bearish Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0097**	0.0067	0.051	$TE_{R_m \to TV}$	0.0090	0.000	0.387
$TE_{TV \to R_m}$	0.0177***	0.0111	0.000	$TE_{TV \to R_m}$	0.0159	0.0035	0.130
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0038	0.0053	0.0066	$TE_{R_m \to TV}$	0.0060	0.0081	0.0108
$TE_{TV \to R_m}$	0.0048	0.0061	0.0078	$TE_{TV \to R_m}$	0.0074	0.0102	0.0132
Bullish Market				Crisis Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0088	0.0000	0.457	$TE_{R_m \to TV}$	0.0323	0.0074	0.237
$TE_{TV \to R_m}$	0.0425***	0.0314	0.000	$TE_{TV \to R_m}$	0.0392	0.0125	0.137
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0063	0.0085	0.0110	$TE_{R_m \to TV}$	0.0085	0.0188	0.0304
$TE_{TV \to R_m}$	0.0070	0.0095	0.0128	$TE_{TV \to R_m}$	0.0114	0.0178	0.0288
Extended Market				COVID-19 Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0064	0.000	0.933	$TE_{R_m \to TV}$	0.0266	0.0080	0.147
$TE_{TV \to R_m}$	0.0158	0.000	0.377	$TE_{TV \to R_m}$	0.0135	0.0000	0.583

Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0105	0.0147	0.0198	$TE_{R_m \to TV}$	0.0102	0.0158	0.0216
$TE_{TV \to R_m}$	0.0107	0.0138	0.0191	$TE_{TV \to R_m}$	0.0116	0.0149	0.0207

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

5.8.8.6 Examining the asymmetrical relationship between unexpected market returns and market trading volume using Transfer Entropy Model: Under Down Market Condition

Overconfidence bias, by focusing on the unexpected returns component, may more likely be present in the equity market in negative market returns condition. The transfer entropy results in Table 5.18 reveal that unexpected market returns can significantly impact trading volumes in overall market during down market returns, implying that investors may overreact to unexpected losses while continuing to trade actively believing that they are the results of some external factors. The overconfidence-driven trading behavior of investors is also persistent in bullish market, even the market experiences negative returns, attributing to the perceived belief that they are more optimistic about the capability to predict market recovery. A weaker presence of unexpected market returns in the COVID-19 still suggests the presence of overconfidence bias among investors even in the face of unprecedented uncertainty, possibly driven by speculative trading or attempts to buy the dip (trading initiative by investors believing that current market drops are short-term and expected to be recovered in the future).

Table 5.18: Transfer Entropy results with unexpected market returns under down market

Overall Market				Bearish Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0169***	0.0103	0.000	$TE_{R_m \to TV}$	0.0092	0.0024	0.180
$TE_{TV \to R_m}$	0.0120***	0.0071	0.000	$TE_{TV \to R_m}$	0.0187**	0.0101	0.003
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0045	0.0058	0.0072	$TE_{R_m \to TV}$	0.0053	0.0067	0.0085
$TE_{TV \to R_m}$	0.0032	0.0042	0.0054	$TE_{TV \to R_m}$	0.0060	0.0081	0.0099
Bullish Market				Crisis Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0291***	0.0170	0.000	$TE_{R_m \to TV}$	0.0185	0.000	0.543
$TE_{TV \to R_m}$	0.0178	0.0026	0.210	$TE_{TV \to R_m}$	0.0165	0.000	0.503

Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0094	0.0128	0.0164	$TE_{R_m \to TV}$	0.0136	0.0205	0.0300
$TE_{TV \to R_m}$	0.0089	0.0112	0.141	$TE_{TV \to R_m}$	0.0103	0.0166	0.0267
Extended Market				COVID-19 Market			
Direction	TE	ETE	P-value	Direction	TE	ETE	P-value
$TE_{R_m \to TV}$	0.0186	0.0017	0.247	$TE_{R_m \to TV}$	0.0406**	0.0221	0.050
$TE_{TV \to R_m}$	0.0176	0.0001	0.287	$TE_{TV \to R_m}$	0.0298	0.0059	0.233
Bootstrapped TE Quantiles				Bootstrapped TE Quantiles			
Direction	25%	50%	75%	Direction	25%	50%	75%
$TE_{R_m \to TV}$	0.0103	0.0142	0.0186	$TE_{R_m \to TV}$	0.0143	0.0203	0.0287
$TE_{TV \to R_m}$	0.0099	0.0132	0.0785	$TE_{TV \to R_m}$	0.0099	0.0130	0.0220

Notes: $TE_{R_m \to TV}$ denotes the direction of information transfer from market return to trading volume, $TE_{TV \to R_m}$ denotes the direction of information transfer from trading volume to market return. TE and ETE imply the coefficients of transfer entropy and effective transfer entropy, respectively.
** Significant at the 5% level.
*** Significant at the 1% level.

Overconfidence is the representation of investors' tendency to overestimate their knowledge to predict equity market movements, which may lead to an increased level of trading activities. The overconfidence hypothesis is more likely to be manifested in unexpected returns rather than the predictable returns, reinforcing investors precision of overestimation in their predictive capabilities. Our analysis from the transfer entropy explicitly evident the presence of this bias in the overall and bullish market under normal market condition as well as down market movements, suggesting that overconfidence-driven trading behavior prevails in the Bangladesh equity market.

5.8.9 Empirical Results and Discussion from LSTM Model

The LSTM is fitted using historic data in two model variations, namely: the Baseline and the Restricted model. To capture sequential dependencies in market behavior, the LSTM model was trained using rolling overlapping windows (We consider 5-day window). Each window (For example, day 1-5) is followed by a prediction of the next day's trading volume (day 6), and this continues across the entire dataset (from days 2–6 to predict day 7 volume, and so on). It is then compared with actual observed volumes to determine whether the volumes predicted are correct (any error). To assess overconfidence bias, two models were evaluated: (i) a baseline model using only past trading volumes, and (ii) a model including both past volumes and market returns. The effectiveness of predictive ability of each model is evaluated by the mean squared error (MSE), where a lower MSE in the Restricted model signifies that market contains sufficient information to predict trading volume, confirming the existence of overconfidence bias.

5.8.9.1 LSTM Model Estimation Focusing on Total Market Return

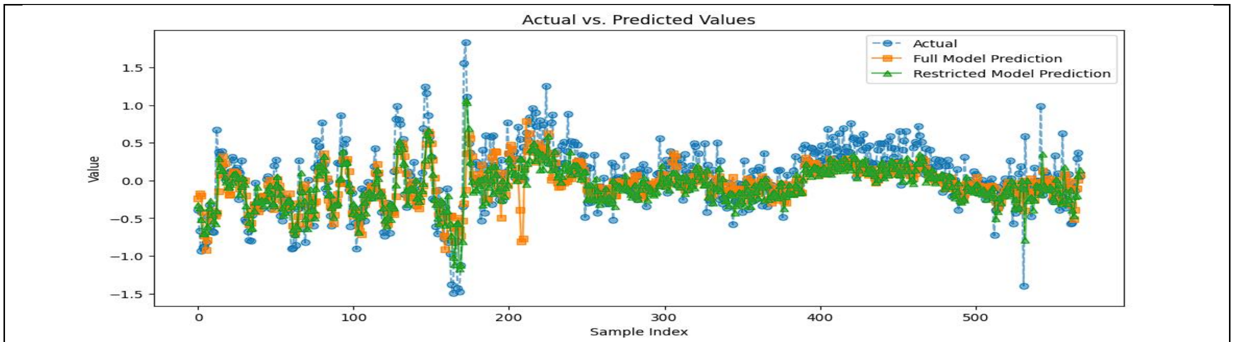
Table 5.19: LSTM Model Performance focusing on Total Market Returns

Market State	**Baseline Model**	**Restricted Model**	**Delta MSE**	**Model with Lower MSE**
Overall	0.12673 (0.2971)	0.10918 (0.3962)	-0.01755	Restricted
Bearish	0.15566 (0.1779)	0.08874 (0.5366)	-0.06692	Restricted
Bullish	0.08673 (0.1499)	0.10115 (0.0091)	0.01442	Baseline
Crisis	0.63706 (0.1867)	0.43336 (0.4852)	-0.20369	Restricted
Extended Crisis	89.307 (-2.901)	44.753 (-1.461)	-44.5554	Restricted
COVID-19	0.10431 (-0.1239)	0.10013 (-0.0789)	-0.00417	Restricted

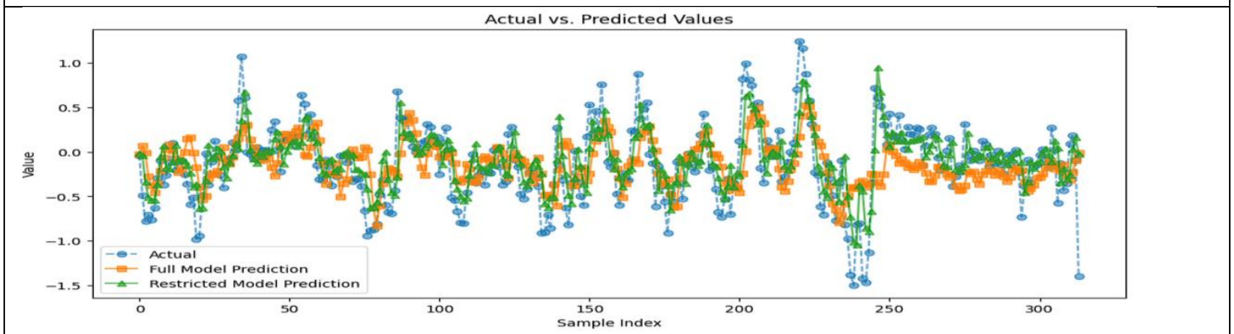
Note: The LSTM model is estimated to have two variations. Baseline model that incorporates only lagged market trading volume, whereas the Restricted model considers lagged market total returns as well as trading volume as inputs feature. Delta MSE (Mean Square Error) measures the difference in MSE between the Restricted and the Baseline models. A negative MSE indicates model's prediction accuracy, confirming overconfidence bias.
Source: Author's Estimation using Python.

The results of the LSTM in Table 5.19 illustrate the key insights into predictive correlation between historical market returns and trading volumes, bringing evidence of overconfidence bias that may prevail across market states. According to the findings, a lower Mean Squared Error (MSE) is observed for the Restricted model relative to the Baseline model in the overall, bearish, and crisis markets, reflecting a better fit to the data. The MSE reduction is consistent with overconfidence theory, which claims that the past market returns contain valuable information to predict future trading activity. The higher squared value in the Restricted model further improves the model's explanatory power and efficiency in predicting trading volume, confirming overconfidence bias in these market states. However, the Restricted model performs worse than the Baseline model in the bullish market, as evidenced by the positive delta MSE.

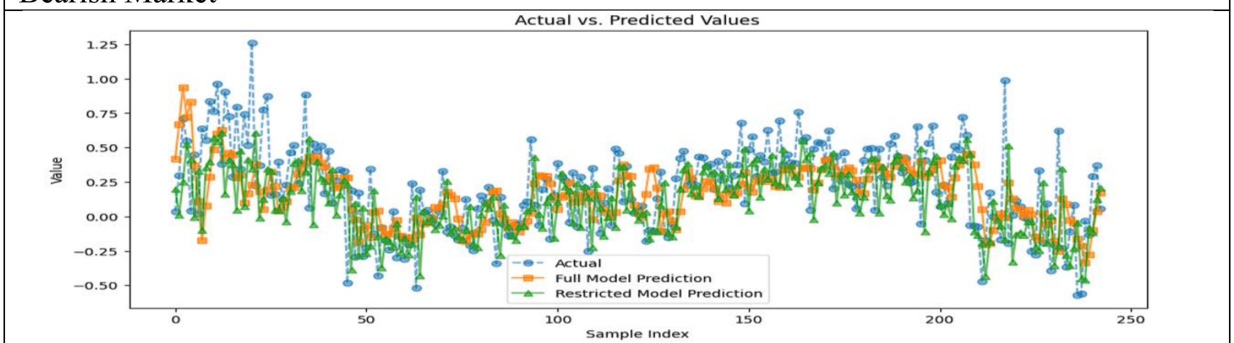
Although negative delta MSE conforms to the improved prediction accuracy in the extended crisis and COVID-19 markets, but the negative R square suggests that model may struggle to explain the relationship between market return and trading volume under both crises' conditions, supporting the absence of overconfidence bias.



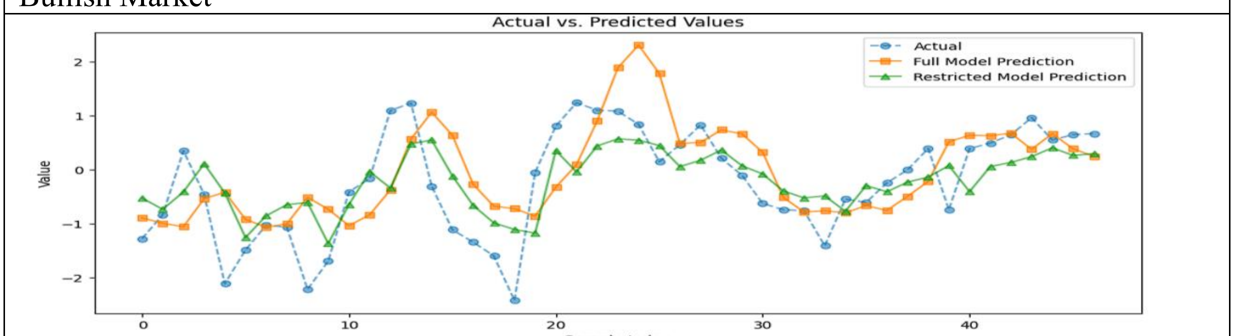
Overall Market



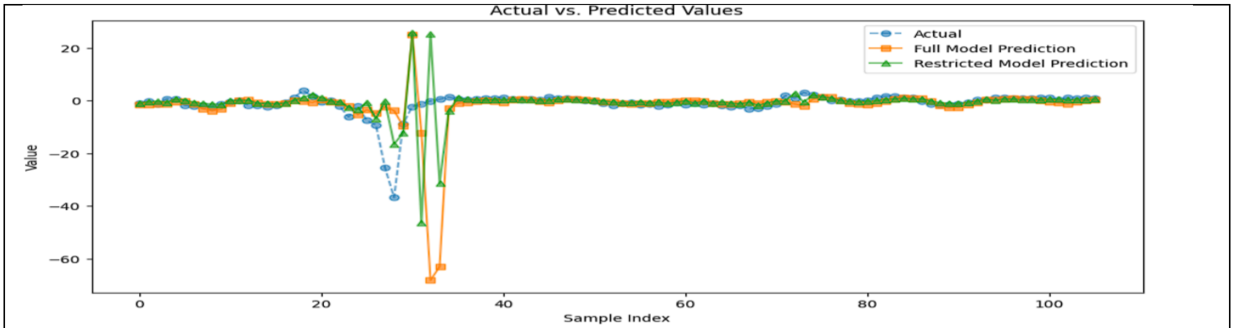
Bearish Market



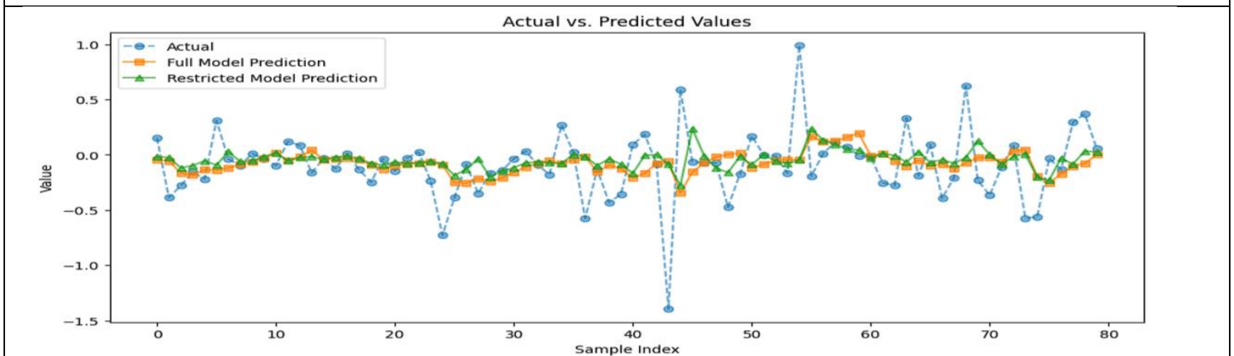
Bullish Market



Crisis Market



Extended Crisis Market



COVID-19 Market

Figure 5.7: Actual and Predicted Trading Volume for Baseline and Restricted LSTM Models using Total Market Returns

The results of the LSTM using total market returns, presented in Table 5.19, are now visualized to give an improved understanding of the model's prediction capability. The objective of the graphical presentation is to assess how each model variant predicts market trading volume and compare the relationship between actual values and predicted values. By observing the alignment of predicted values with actual trade volumes, the graph facilitates in determining whether market returns contribute to more precise prediction of trading volume and how various market states influence prediction reliability. Visualization improves the interpretability of the LSTM's findings and enables a more thorough examination of investors' trading dynamics. Figure 5.7 demonstrates that the prediction of the Restricted Model aligns more closely with actual values relative to the Full model prediction for the overall, bearish and crisis markets, revealing that past market returns lead to predicting trading volume.

5.8.9.2 LSTM Model Estimation Focusing on Unexpected Market Return

To further investigate overconfidence hypothesis, the essay expands the analysis by incorporating the unexpected market return component, which is derived from the Market Index model. Unlike the total market return, which grabs general market movements, unexpected market returns separate the portion of the market return that departs from expected market performance, therefore offering a more realistic indicator of investor overconfidence. We re-estimated the LSTM model to this refined unexpected return component to better capture the unpredictable portion of the equity market returns and investors' irrationality across different market states. The study aims to measure whether trading volume remains dependent on past return patterns when predictable market return component was eliminated. Table 5.20 reports the results of the LSTM model focusing on the unexpected return component, providing deeper insights into investor psychology and market dynamics.

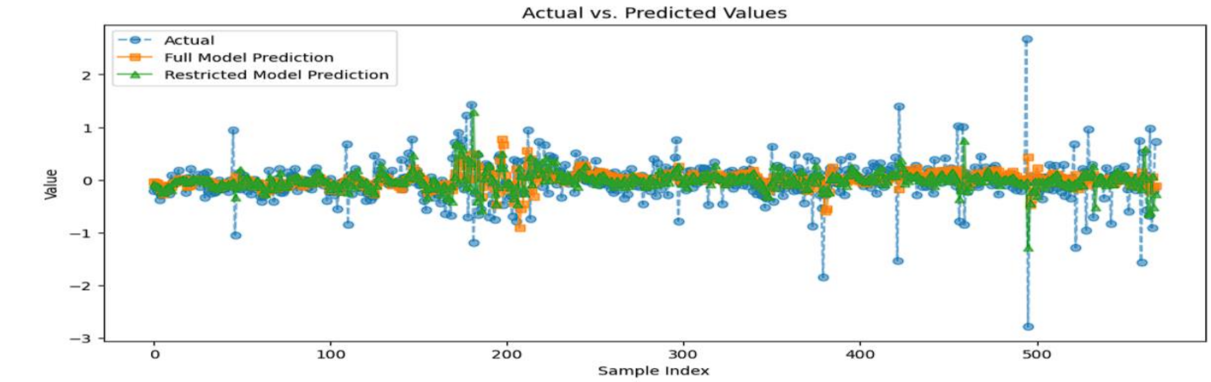
Table 5.20: LSTM Model Performance focusing on Unexpected Market Return

Market states	Baseline Model	Restricted Model	Delta MSE	Model with Lower MSE
Overall	0.16646 (0.1773)	0.15396 (0.0853)	-0.01250	Restricted
Bearish	0.17693 (-0.4413)	0.12075 (0.0282)	-0.05618	Restricted
Bullish	0.25498 (-0.8324)	0.30260 (-1.280)	0.04761	Baseline
Crisis	0.13030 (-0.1314)	0.07147 (0.3852)	-0.05883	Restricted
Extended Crisis	2.5639 (-1.739)	0.72703 (0.2205)	-1.8369	Restricted
COVID-19	0.35501 (0.0288)	0.52040 (-0.5627)	0.16538	Restricted

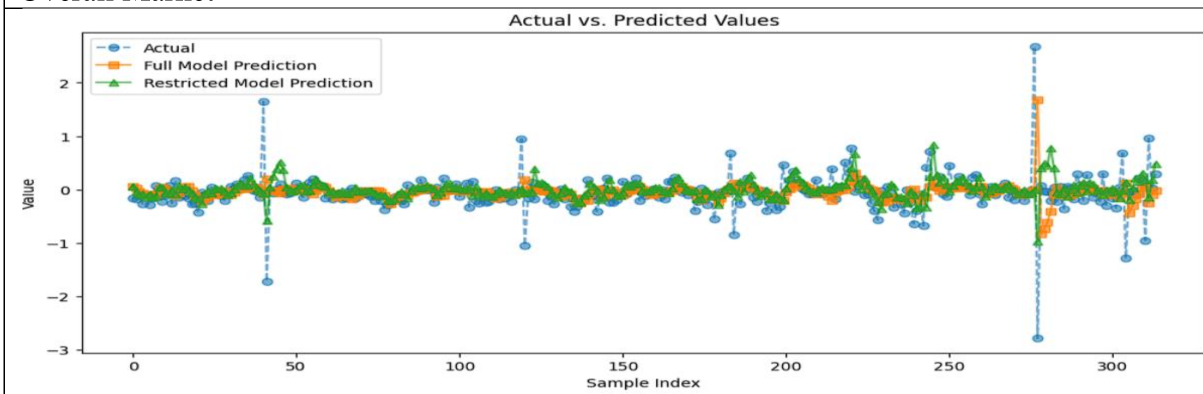
Note: The LSTM model is estimated to have two variations. Baseline model incorporates only lagged market trading volume, whereas the Restricted model considers lagged market unexpected returns as well as trading volume as inputs feature. Delta MSE (Mean Square Error) measures the difference in MSE between the Restricted and the Baseline models. A negative MSE indicates model's prediction accuracy, confirming overconfidence bias.
Source: Author's Estimation using Python.

The results show that delta MSE is negative for all market states except for the bullish and COVID-19 markets. This implies the Restricted LSTM model outperforms the Baseline model in these market phases, highlighting that unexpected return provides predictive power over market trading volume. Further, the positive R square values validate those unexpected returns improves the Restricted LSTM model's explanatory power, conforming overconfidence theory. It is also noticeable that R square values for the overall and bearish markets are relatively lower than those obtained in the estimation of total market return. In addition, the evidence of overconfident bias in the extended crisis market signals that unexpected market returns capture surprises and shocks that investors may overreact. This suggests that in prolonged periods of market stress, investors may grow more overconfident, responding to unexpected market return variations rather than rationally evaluating equity market fundamentals.

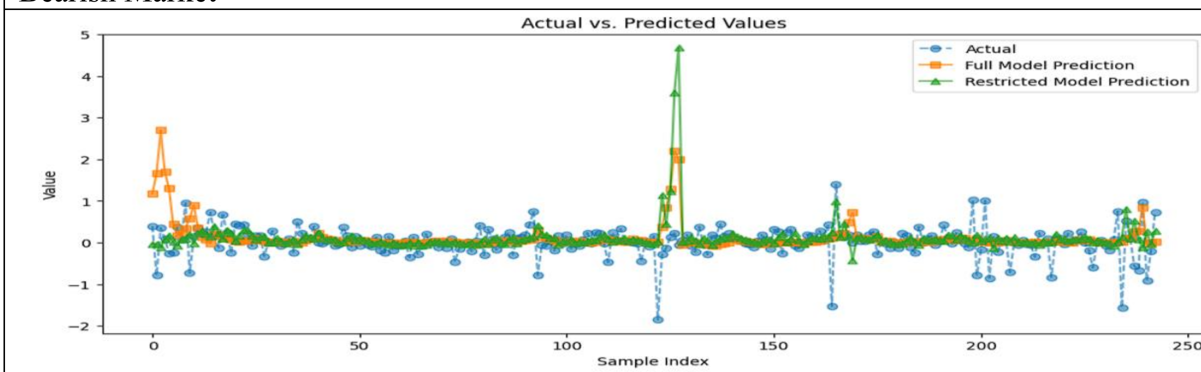
The positive delta MSE in the bullish and the COVID-19 markets indicate that unexpected market returns alone may not improve the predictive accuracy of trading volume. Furthermore, the negative R square value confirms that the model fails to perform well than simply predicting the mean trading volume in these markets.



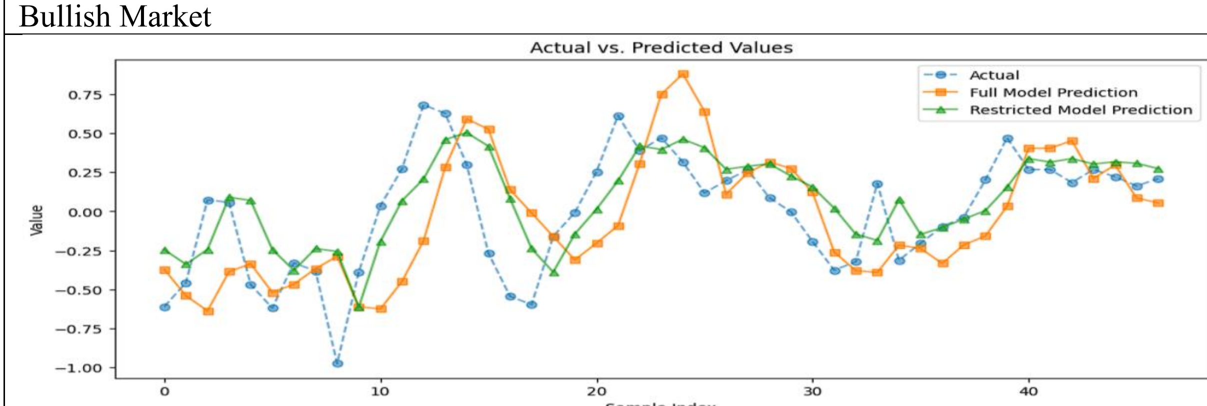
Overall Market



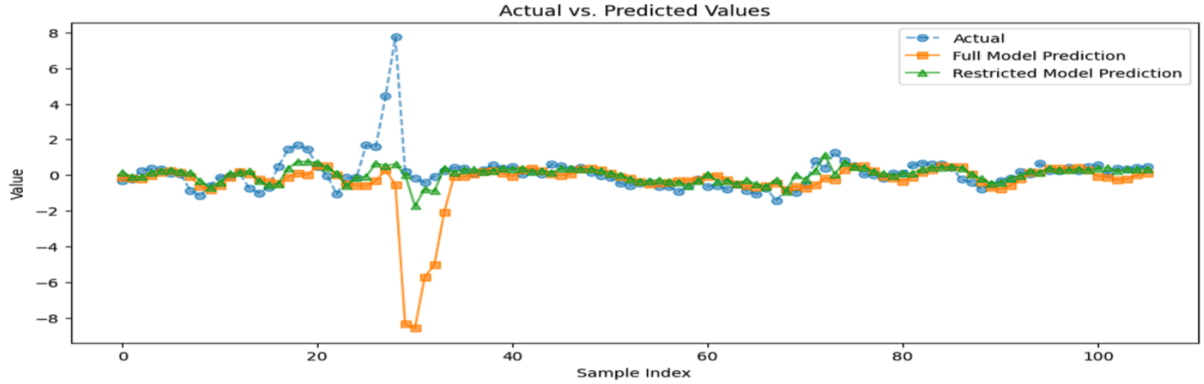
Bearish Market



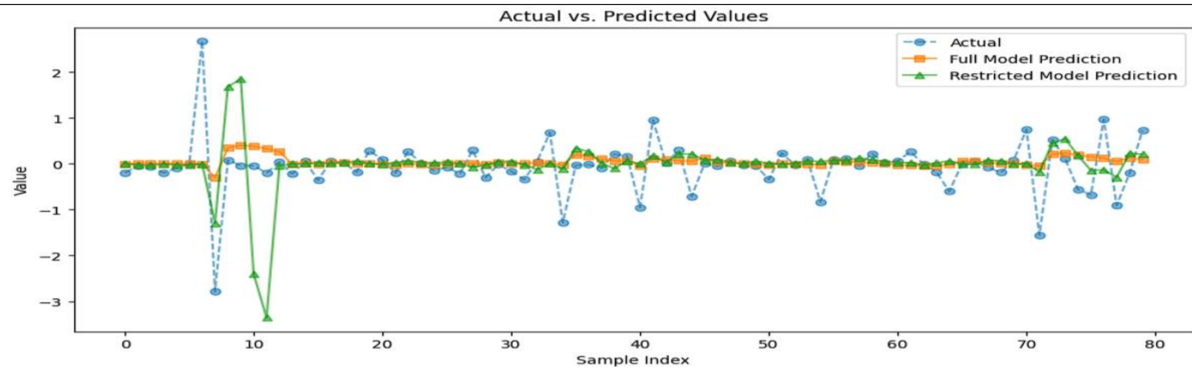
Bullish Market



Crisis Market



Extended Crisis Market



COVID-19 Market

Figure 5.8: Actual and Predicted Trading Volume for Baseline and Restricted LSTM Models using Unexpected Market Returns

Figure 5.8 also shows the LSTM results when estimated using unexpected market returns. This graph illustrates how the restricted model prediction is closely matched with actual values in case of the overall, bearish, crisis and extended crisis markets, supporting overconfidence bias where investors base their trading decisions on past market returns, resulting in their increased trading activities.

Estimating LSTM model using total market returns highlight that investor overconfidence in the Bangladesh equity market vary with the nature of market states, with stronger effects in crisis and bearish markets, where investor psychology, market sentiment, risk perception, and liquidity constraints drive traders to rely on past market behavior. In contrast, bullish, extended crisis and COVID-19 markets do not exhibit the predictive connection between market returns and trading volumes as investors decisions are represented by more stable trading behaviors.

The LSTM findings focusing on the unexpected market returns component offer an additional insight into the role of overconfidence bias in reshaping investor behavior under different market states. This machine learning model when estimated by incorporating unexpected market returns demonstrated superior predictive accuracy in the overall, bearish, crisis, and extended crisis markets. The results reflect the overconfidence hypothesis, which proposes that unexpected return is likely perceived as a signal of mispricing or a new trend that may lead to overconfident trading behavior, particularly in stress and downturn market conditions (Daniel, Hirshleifer, & Subrahmanyam, 1998). This behavior suggests that investors continue to trade excessively, underestimating risk and overestimating their capability to predict market movements even during the prolonged market downturns.

The LSTM model performed worse in a bullish market phase, suggesting absence of overconfidence bias during an upward market trend. It could be possible that the investors are much more momentum driven and investors are less into speculative trading and just want to stay with the investment there is to, relatively to lower trading activity. The absence of overconfidence during the global unprecedented healthcare pandemic suggests that market participants may choose to adopt the passive trading strategy, which lead investors to focus on liquidity and market stability rather than being overly speculative.

5.8.9.3 Credibility and Validation of LSTM Findings

In an effort to justify the strength and validity of the LSTM's findings, the results were compared to the outcomes achieved using the Vector Autoregressive (VAR) and Transfer Entropy models. The VAR model focuses on linear dependence, and the Transfer Entropy method determines the existence of non-linear and asymmetric information responses. The fact that overconfidence bias was identified in all the three models, especially in the overall and bearish markets as well as crisis markets supports the validity and stability of the empirical findings.

This is the important benchmark of the VAR results as they show that historical market returns carry an important predictor of trading volume in many lags, an indication of overconfidence hypothesis. These results are also supported by Transfer Entropy which indicates the flow of directional information between returns and volume, as well as identifying dependencies that traditional linear models might fail. LSTM strongly fits on learning complicated long-term temporal dependencies and confirming predictive capability even in volatile market environments.

Evidence of findings convergence across linear, non-linear, and deep learning approaches can minimize issues of model-specific over-fitting, and the behavioral inferences become more credible. Also, the train-test splits and the comparison of the Mean Squared Error (MSE) of the LSTM model were used as stability measures. The outstanding results of the Restricted model in most states of the market confirm the idea that market returns have significant predictive value to trading volume, which is evidence of the strength of the overconfidence hypothesis.

5.8.10 Examination of overconfidence at the Industry Level

The existing literature has predominantly investigated overconfidence bias using aggregate market data, focusing on the connection between market return and trading volume. These existing studies provide compelling evidence that past market returns drive trading volumes, confirming the idea that investors become overconfident following profitable market returns. However, equity markets are heterogeneous, with industry-specific attributes may affect investor behavior. In spite of this, very few studies have examined overconfidence bias at the industry level, particularly in the context of frontier equity markets.

Industries may differ due to variations in risk exposure, investor composition, and regulatory compliance, which may exhibit the differences in the intensity of overconfidence bias across industries. Analyzing overconfidence bias at the industry level, we can develop deeper insights into whether the behavior of investors is driven by broader market trends or industry-specific traits.

This study tries to fill this gap by systematically examining overconfidence bias within different industries. By employing well-established vector autoregressive (VAR) framework to industry-level data, we intend to determine whether the correlation between past market returns, and trading volume holds across the sectors. The findings may provide valuable insights into how industry dynamics play a role in shaping investor behavior and advance knowledge of market efficiency and psychological biases in the equity market.

Table 5.21: Empirical Results from VAR model for the Whole Market

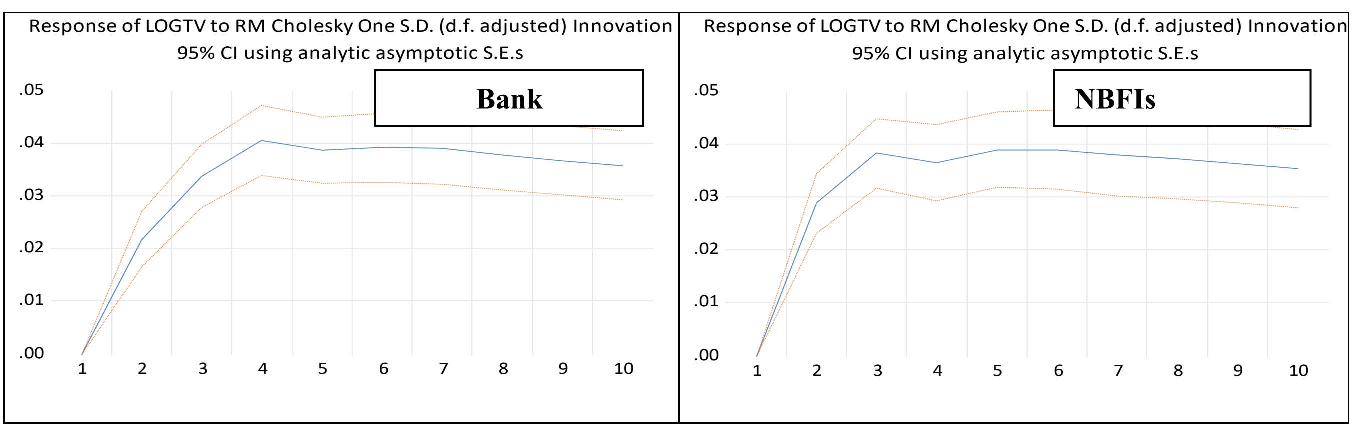
	Bank	NBFIs	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.579***	0.557***	0.601***	0.622***	0.469***	0.661***	0.516***
TV(-2)	0.174***	0.213***	0.143***	0.152***	0.201***	0.181***	0.224***
TV(-3)	0.194***	0.184***	0.211***	0.167***	0.240***	0.108***	0.181***
R_m(-1)	0.015***	0.019***	0.025***	0.012***	0.012***	0.018***	0.015***
R_m(-2)	0.012***	0.010***	0.014***	0.010***	0.010***	0.010***	0.010***
R_m(-3)	0.008***	-0.000	0.004	0.011***	0.008***	0.000***	0.005***
Constant	0.452***	0.373***	0.339***	0.505***	0.761***	0.406***	0.669***
CSAD	-0.000	0.000	0.011***	0.000	0.003	0.003***	0.003***
CSAD(-1)	-0.002	-0.001	-0.001	-0.003	0.002	0.004***	-0.000
CSAD(-2)	0.004***	0.002	0.008	0.000	-0.001	-0.002	0.002
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.346***	0.558***	0.550***	0.598***	0.421***	0.413***	0.547***
TV(-2)	0.254***	0.232***	0.190***	0.126***	0.294***	0.259***	0.162***
TV(-3)	0.265***	0.156***	0.193***	0.192***	0.210***	0.232***	0.228***
R_m(-1)	0.012***	0.014***	0.150***	0.000	0.102**	0.014***	0.006***
R_m(-2)	0.016***	0.011***	0.014***	0.005***	0.001	0.026***	0.005***
R_m(-3)	0.001	-0.003	0.013***	0.009***	-0.001	0.006***	0.008***
Constant	1.09***	0.403***	0.491***	0.604***	0.531***	0.726***	0.445***
CSAD	0.001	0.000	0.011***	0.008***	0.006***	0.015***	0.006
CSAD(-1)	-0.008	-0.005	-0.002	0.002	0.005***	0.007	0.008***
CSAD(-2)	0.008***	0.007***	0.001	0.000	-0.000	-0.012***	-0.001

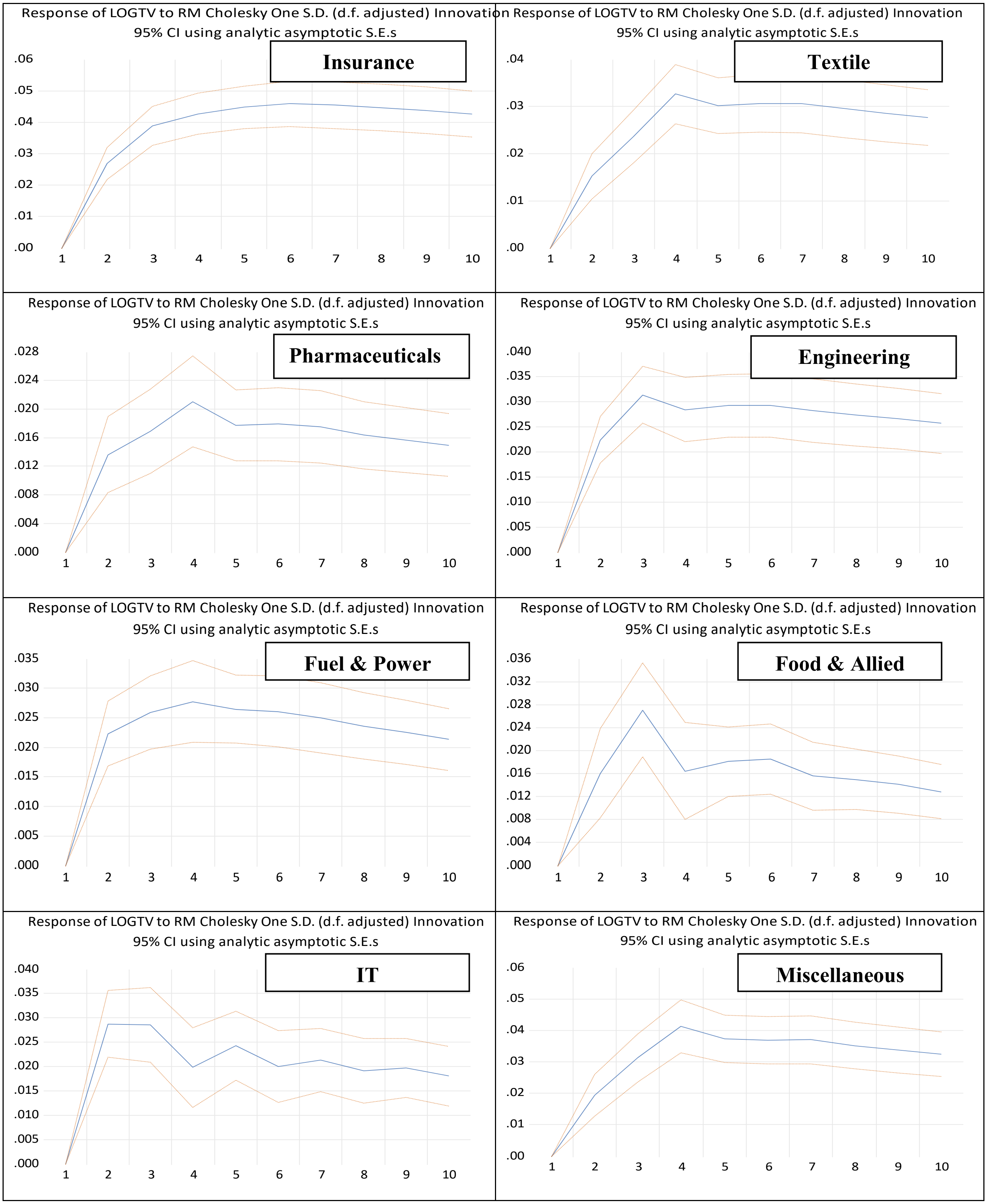
Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level

*Significant at the 10% level.
Source: Author's Own Calculation.

The overconfidence theory suggests that investors become more confident in their trading strategy if they believe that past market gains indicate future profitability, which results in increased trading activity. The study extends the analysis to industry level to determine whether overconfidence is evident across industries, a field that remains underexplored, especially in frontier equity markets. Using industry-level data, we examined how the effect of past industry returns impact trading volume in each industry by applying vector autoregressive (VAR) model. The findings indicate that overconfidence bias is prevalent in the Bangladesh equity market in almost all industries, except for the Tannery industry. Specially, eight industries reveal strong evidence of overconfidence bias, since each lagged market return is statistically significant at the 1 percent level. This implies that past market returns seem to have persistent and significant impact on trading volume, reinforcing investors' behavioral tendency in these industries to engage in more trading activity due to their belief in predictive capabilities. In addition, five industries exhibit two significant lagged market returns, supporting the evidence of overconfidence theory, although to a slightly lesser extent. Different industries demonstrate the varying degree of significant overconfidence bias, suggesting that the bias is not uniform rather dependent on industry-specific attributes like investor composition, market liquidity, and information asymmetry. The Tannery industry does not exhibit the presence of overconfidence bias, which may result from lower investor participation, a more informed investor base, and lower industry-level liquidity, having aggregate effects on reducing speculative trading behavior.

In summary, the findings of persistent overconfidence at the industry level in the Bangladesh equity market provide robust empirical evidence, confirming that investors overreact to past return trends, contributing to speculative trading behavior. These findings offer insights into industry-specific behavioral patterns by emphasizing the differences in investors overconfidence across sectors, while prior research primarily concentrated on aggregated market trends.




Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Insurance
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Textile
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Pharmaceuticals
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Engineering
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Fuel & Power
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Food & Allied
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
IT
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Miscellaneous

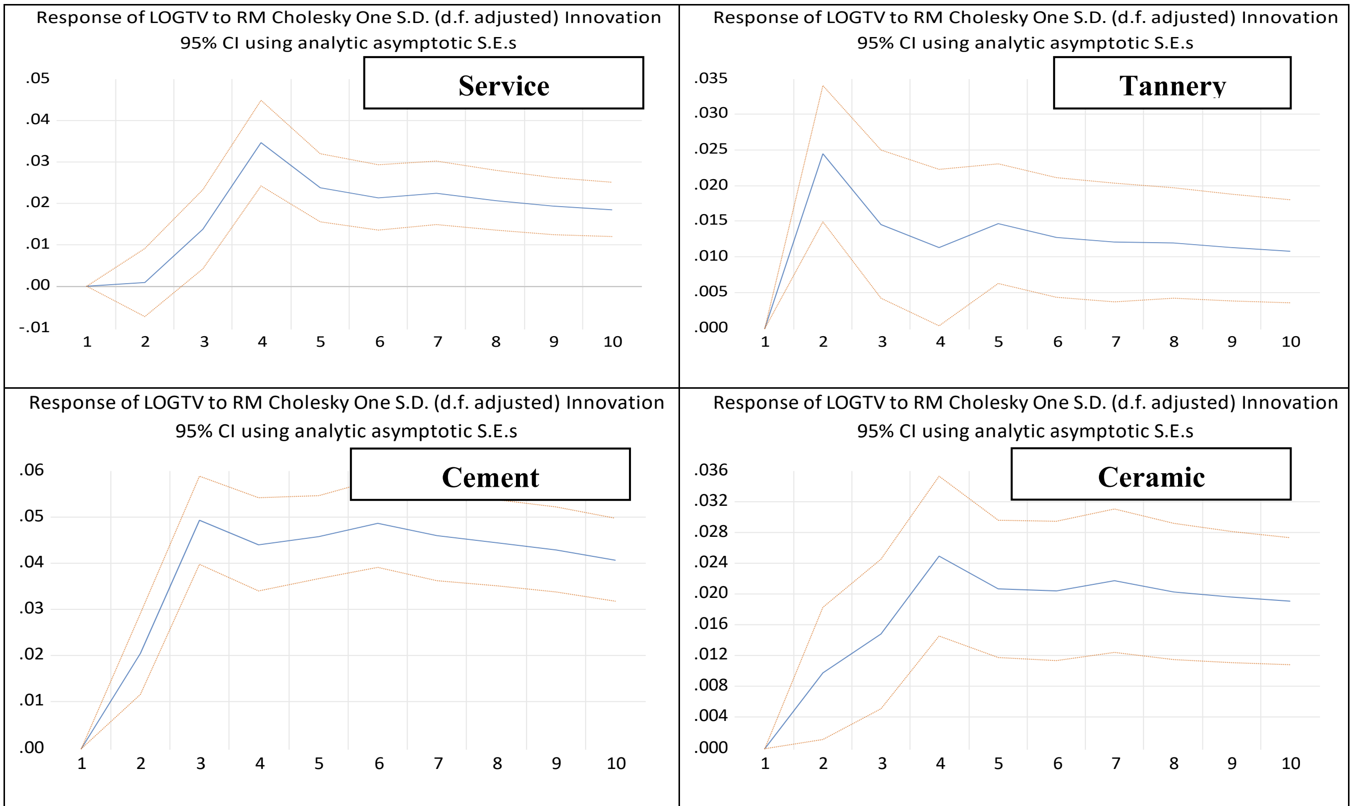


Figure 5.9: Impulse Response of Trading Volume to Market Returns for the Whole Market

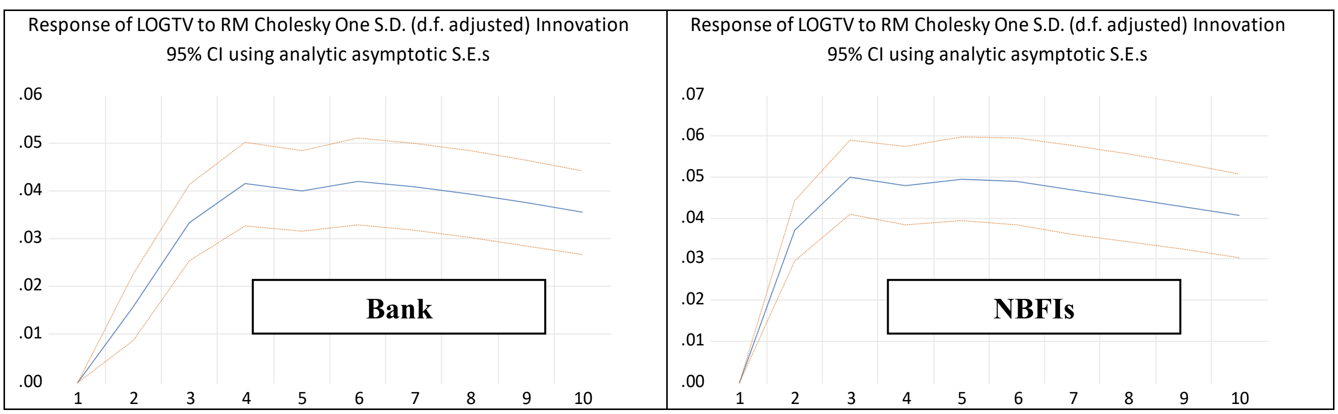
Table 5.22 : Empirical Results from VAR model for the Bearish Market

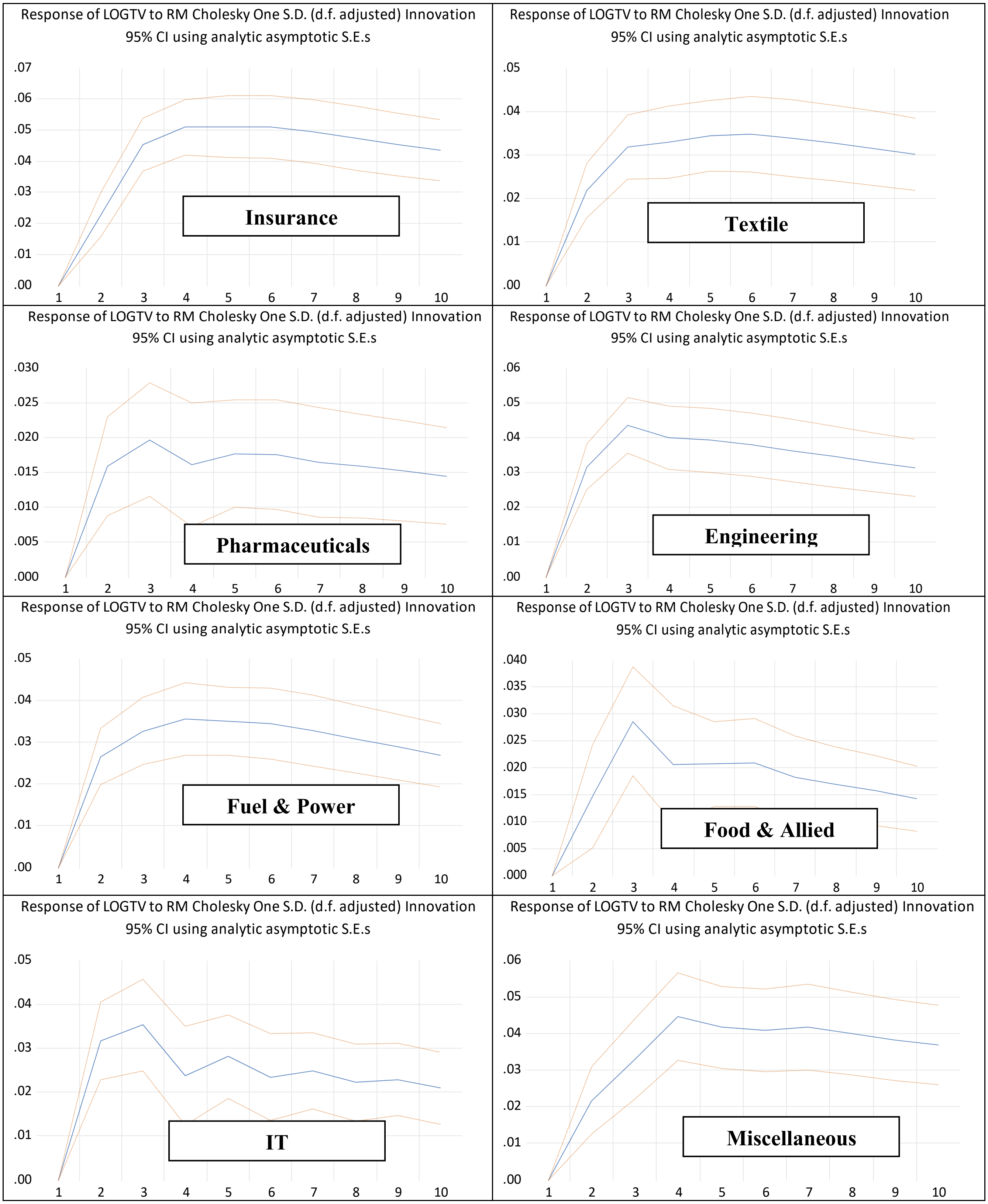
	Bank	NBFIs	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.578***	0.613***	0.678***	0.640***	0.568***	0.656***	0.609***
TV(-2)	0.189***	0.147***	0.033***	0.160***	0.153***	o.187***	0.110***
TV(-3)	0.160***	0.170***	0.233***	0.131***	0.203***	0.088***	0.185***
$R_m(-1)$	0.012***	0.027***	0.024***	0.019***	0.015***	0.026***	0.022***
$R_m(-2)$	0.017***	0.009***	0.019***	0.014***	0.009***	0.011***	0.013***
$R_m(-3)$	0.011***	-0.001	0.003	0.004	0.000	-0.000	0.006***
Constant	0.625***	0.554***	0.409***	0.584***	0.647***	0.558***	0.819***
CSAD	0.003	0.006***	0.007	-0.002	0.008***	0.001	0.003
CSAD(-1)	-0.004	0.003	-0.007	0.005	-0.003	0.013***	-0.008***
CSAD(-2)	0.008***	0.004	0.023***	0.004	-0.004	0.003	0.006***
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.379***	0.598***	0.614***	0.576***	0.492***	0.483***	0.510***
TV(-2)	0.278***	0.199***	0.116***	0.088***	0.269***	0.223***	0.211***
TV(-3)	0.204***	0.148***	0.209***	0.212***	0.182***	0.192***	0.221***
$R_m(-1)$	0.013***	0.014***	0.016***	0.004	0.015	0.012***	0.005
$R_m(-2)$	0.020***	0.011***	0.012***	0.013***	-0.002	0.023***	0.007***

$R_m(-3)$	0.005	-0.003	0.013***	0.020***	-0.003	0.007***	0.011***
Constant	1.13***	0.417***	0.452***	0.876***	0.396***	0.751***	0.427***
CSAD	0.008	0.003	0.011***	0.004	0.003	0.019***	0.000
CSAD(-1)	-0.016	-0.009	-0.004	0.007	0.010***	0.011	0.009
CSAD(-2)	0.006	0.008***	0.006	0.010	-0.003	-0.005	0.002

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level
*Significant at the 10% level.
Source: Author's Own Calculation.

By classifying bearish market based on Dow Theory, the study provides more accurate identification of declining market phase by capturing intermediate trends. This methodological orientation strengthens the robustness of the findings to guarantee a systematic and objective classification of equity market state. The VAR results from the bearish market reported in Table 5.22 are aligned closely with those obtained in the overall market, supporting that overconfidence bias persists in all sectors of the equity market except Tannery sector. The persistent effects of past industry return on trading activity suggest that investors continue to overestimate their predictive power and participate in more active trading, even on a downturn in market condition. Findings reiterate that investors may potentially exploit perceived undervaluation or short-term market price corrections. This further emphasizes that investor behavior is not entirely dictated by rational expectations but also by psychological factors, which reinforces the behavioral finance theory that investors are not always able to learn from their mistakes.




Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Insurance
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Textile
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Pharmaceuticals
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Engineering
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Fuel & Power
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Food & Allied
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
IT
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Miscellaneous

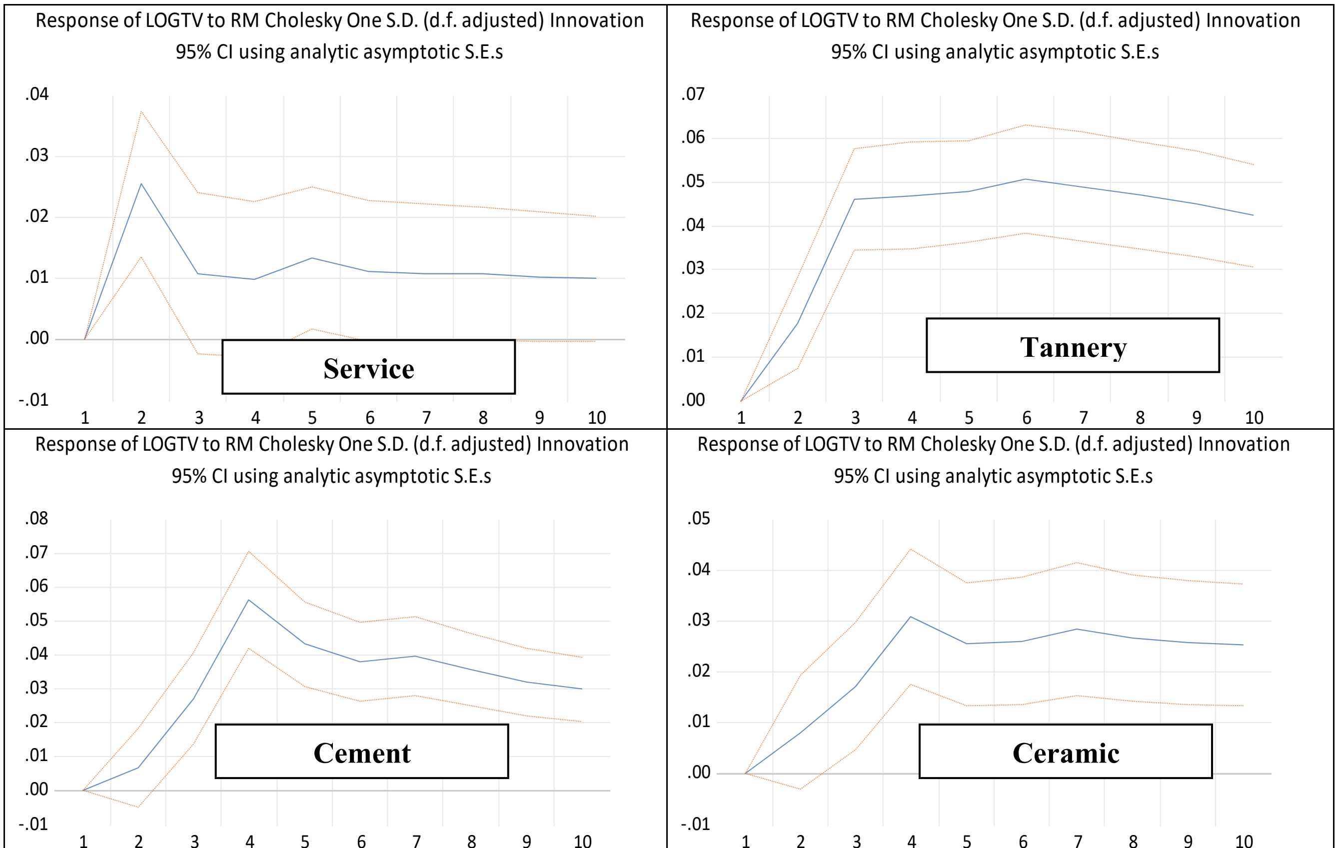


Figure 5.10: Impulse Response of Trading Volume to Market Returns for the Bearish Market

Table 5.23: Empirical Results from VAR model for the Bullish Market

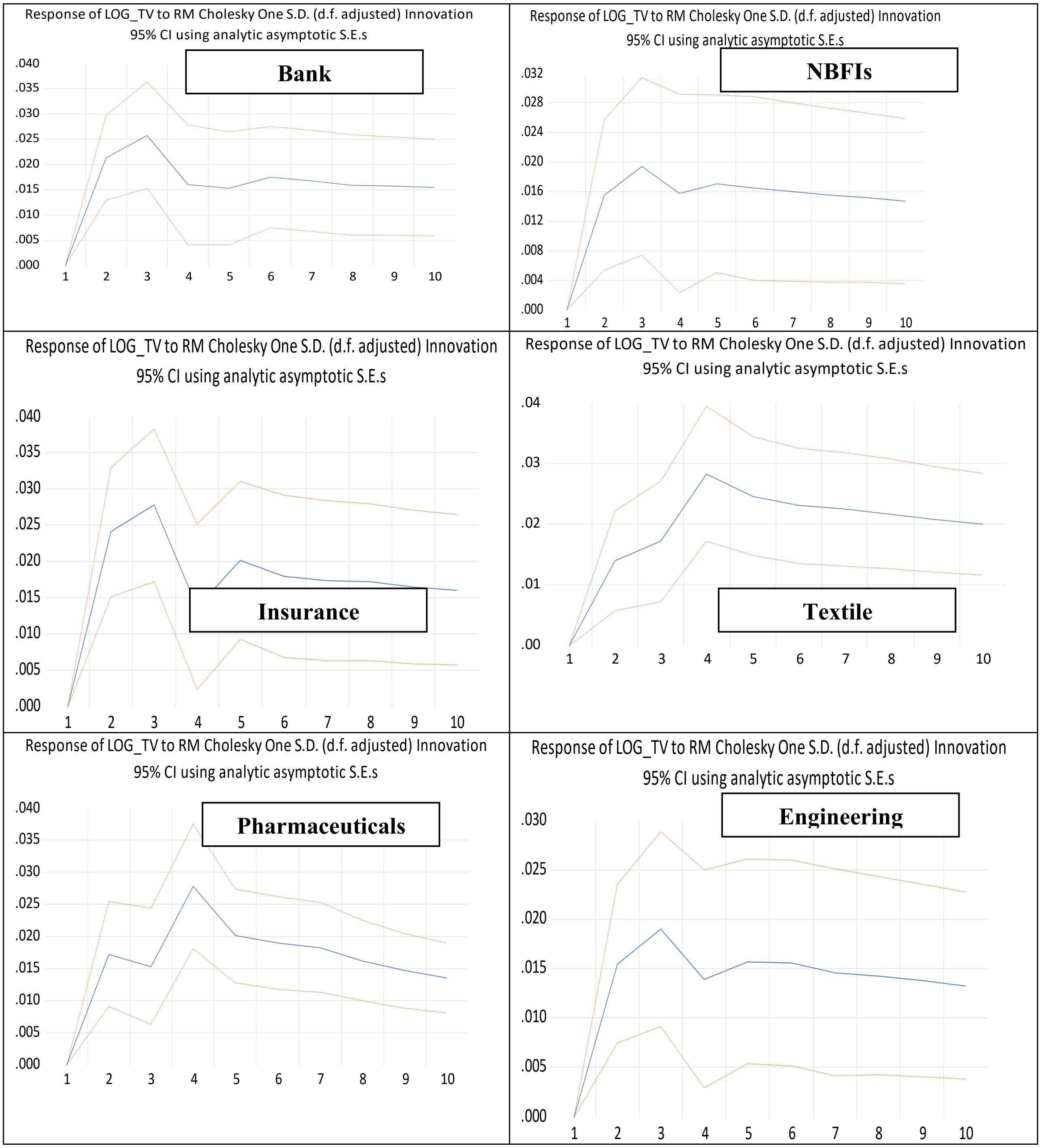
	Bank	NB	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.750***	0.639***	0.635***	0.669***	0.470***	0.722***	0.472***
TV(-2)	0.042	0.198***	0.227***	0.091***	0.162***	0.139***	0.323***
TV(-3)	0.172***	0.122***	0.099***	0.178***	0.221***	0.089***	0.129***
$R_m(-1)$	0.015***	0.009***	0.022***	0.010***	0.017***	0.013***	0.112***
$R_m(-2)$	0.004	0.006	0.011***	0.005	0.007	0.005	0.007***
$R_m(-3)$	-0.002	-0.001	-0.012	0.011***	0.015***	-0.002	0.002
Constant	0.324***	0.351***	0.309***	0.529***	1.355***	0.422***	0.626***
CSAD	0.002	-0.003	0.013***	-0.006	-0.003	0.003	0.005***
CSAD(-1)	0.008	-0.000	0.000	0.002	0.004	0.002	0.005
CSAD(-2)	-0.006	0.000	-0.004	-0.002	-0.000	-0.006***	0.002
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.412***	0.639***	0.503***	0.634***	0.391***	0.483***	0.623***
TV(-2)	0.190***	0.185***	0.277***	0.173***	0.290***	0.229***	0.120***
TV(-3)	0.261***	0.126***	0.147***	0.124***	0.203***	0.178***	0.179***

$R_m(-1)$	0.007	0.010***	0.013***	-0.001	0.011***	0.017***	0.009***
$R_m(-2)$	0.010***	0.005	0.016***	0.002	0.001	0.024***	0.004
$R_m(-3)$	-0.002	-0.004	0.012***	0.006***	-0.001	0.014***	0.008**
Constant	1.058***	0.374***	0.537***	0.512***	0.588***	0.874***	0.552
CSAD	0.007***	-0.001	0.010	0.004***	0.008***	0.003	0.009
CSAD(-1)	-0.003	-0.000	-0.001	0.003	0.004	-0.011	0.008
CSAD(-2)	0.012***	0.004	0.004	-0.000	-0.008	0.003	-0.005

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level
*Significant at the 10% level.
Source: Author's Own Calculation.

The study also empirically examines overconfidence bias in the bullish market, which is classified applying Dow Theory to ensure a systematic and precise analysis of how investor sentiment reshaping their trading behavior specifically within the periods of sustained market upswings. Bullish market VAR results shown in Table 5.23 largely mirror those observed in the overall and bearish markets, which confirms that in almost every industry except Tannery, past industry significantly influence trading volumes. Unlike the overall and bearish markets, one notable difference in the bullish market is that past industry returns are significant for one or two lags in most industries except the Miscellaneous and Cement industries where all lags are significant.

The prevalence of overconfidence bias in the bullish market may align with the behavioral theory that investor behavior is driven by optimism and momentum, causing an initial surge in trading activity as they pursue to capitalize on market price increases. However, as bullish trends continue, the impact of past industry returns may fade, and trading activities stabilize since investors grow more confident in the market's sustained upward trends. This contrasts with bearish market where market uncertainty and fear might result in a more prolonged response to past industry returns, leading to a higher level of overconfidence-driven trading activity over the long term. One key finding from bullish market results demonstrates that only Miscellaneous and Service industries have a significant influence on past industry returns across all lag periods. This may result due to industry-specific factors, which make investor sentiment more sensitive to past industry price movements.


Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Bank
.040
.035
.030
.025
.020
.015
.010
.005
.000
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
NBFIs
.032
.028
.024
.020
.016
.012
.008
.004
.000
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Insurance
.040
.035
.030
.025
.020
.015
.010
.005
.000
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Textile
.04
.03
.02
.01
.00
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Pharmaceuticals
.040
.035
.030
.025
.020
.015
.010
.005
.000
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Engineering
.030
.025
.020
.015
.010
.005
.000
1 2 3 4 5 6 7 8 9 10


Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Fuel & Power
.032 .028 .024 .020 .016 .012 .008 .004 .000
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Food & Allied
.032 .028 .024 .020 .016 .012 .008 .004 .000 -.004 -.008
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
IT
.030 .025 .020 .015 .010 .005 .000 -.005
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Miscellaneous
.05 .04 .03 .02 .01 .00
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Service
.05 .04 .03 .02 .01 .00 -.01 -.02
1 2 3 4 5 6 7 8 9 10
Response of LOG_TV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Tannery
.05 .04 .03 .02 .01 .00 -.01 -.02
1 2 3 4 5 6 7 8 9 10

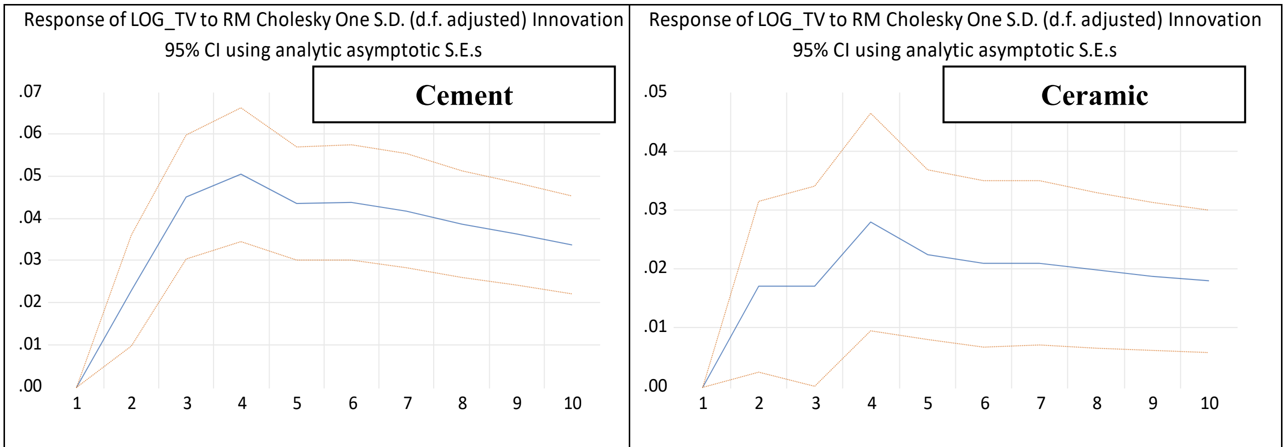


Figure 5.11: Impulse Response of Trading Volume to Market Returns for the Bullish Market

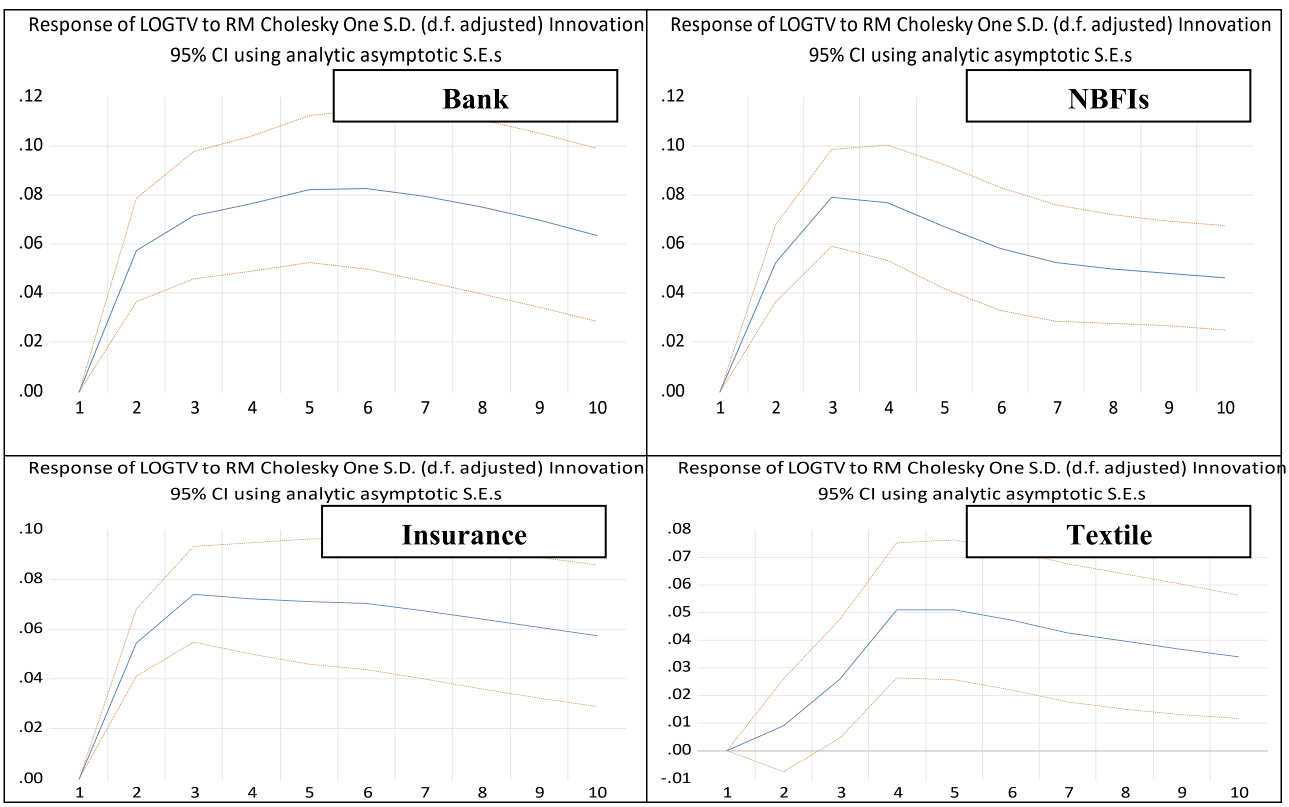
Table 5.24 and 5.25 reports the VAR results for both crisis and extended crisis markets, respectively. The results show that overconfidence bias is prevalent in all industries except the Tannery and Service industries. The remaining industries demonstrate that past industry returns significantly affect trading volume, supporting that investors tend to depend on past performance when making trading decisions even during periods of financial crises. The major distinction from other market states is that no industry confirms significant industry returns for all three lagged periods. These findings are consistent with overconfidence theory, which suggests that investors tend to overestimate their ability to explain market signals, resulting in excessive trading activity based on past performance. In crisis time, equity markets remain highly volatile and uncertain, and investors appear to continually react to past market performance, showing overconfidence-driven trading activity. This persistent overconfidence bias in most industries, even in a market crash situation, implies that investors appear to actively trade based on past industry returns instead of adapting to new market realities. This behavior may align with the illusion of control bias, where investors believe they can predict market reversals despite heightened uncertainty. Nonetheless, the lack of significance of all lag periods imply that overconfidence bias persists less during times of financial crises. It may be linked to the prospect theory, which states that during crisis time investors become more risk averse and may be quicker to devise their trading strategies. There is no evidence of overconfidence bias in the Service and Tannery industries, indicating that investors in these industries behave differently during financial crises. This could be due to a less speculative investor base or lower trading behavior where investors become less reactive to short-term market fluctuations.

Table 5.24: Empirical Results from VAR model for the Crisis Market

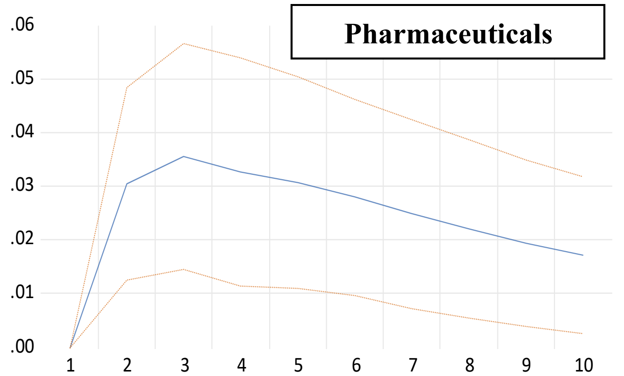
	Bank	NB	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.598***	0.566***	0.774***	0.765***	0.623***	0.691***	0.659***
TV(-2)	0.160***	0.201***	-0.041	0.038	0.006	0.118	0.066
TV(-3)	0.140***	0.153***	0.163***	0.092	0.161***	0.047	0.217***

$R_m(-1)$	0.026***	0.029***	0.023***	0.004	0.021***	0.041***	0.026***
$R_m(-2)$	0.007	0.010***	-0.001	0.007	0.006	0.005	0.005
$R_m(-3)$	0.001	0.002	0.001	0.010***	0.004	-0.002	0.004
Constant	0.818***	0.665***	0.943***	0.873***	1.762***	1.256***	0.471***
CSAD	0.030***	0.001***	0.004***	-0.001	0.018	0.023	0.001
CSAD(-1)	-0.028	0.013	-0.014	0.004	-0.020	-0.022	0.018***
CSAD(-2)	-0.002	0.004	0.003	0.002	-0.000	-0.005	0.003
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.625***	0.655***	0.588***	0.947***	0.571***	0.650***	0.598***
TV(-2)	-0.056	-0.113	0.072	-0.062	0.139	0.116	0.159***
TV(-3)	0.288***	0.242***	0.134***	-0.020	0.194***	0.117	0.139***
$R_m(-1)$	0.024***	0.036***	0.035***	0.010	0.031***	0.020***	0.026***
$R_m(-2)$	0.021	0.022***	-0.001	0.001	-0.003	0.014***	0.007
$R_m(-3)$	0.000	0.008	0.018***	0.000	-0.007	0.000	0.001
Constant	1.197***	1.634***	1.162***	1.049***	0.726***	0.992***	0.818***
CSAD	0.016	0.030	0.027	0.006***	0.023	0.027	0.029***
CSAD(-1)	0.005	-0.011	-0.032	0.011	-0.026***	-0.016	-0.025
CSAD(-2)	-0.022	-0.025	-0.007	-0.002	0.000	-0.022***	-0.002

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level. *Significant at the 10% level.
Source: Author's Own Calculation.



Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s



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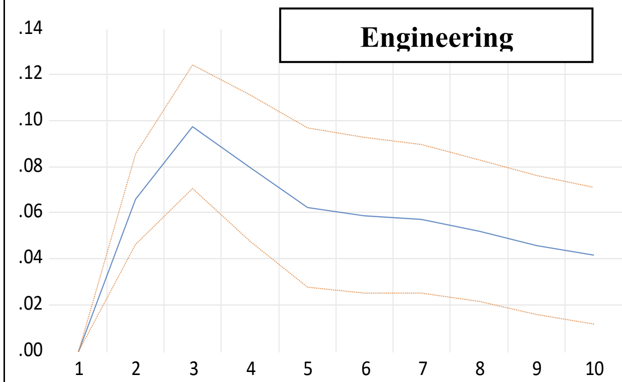

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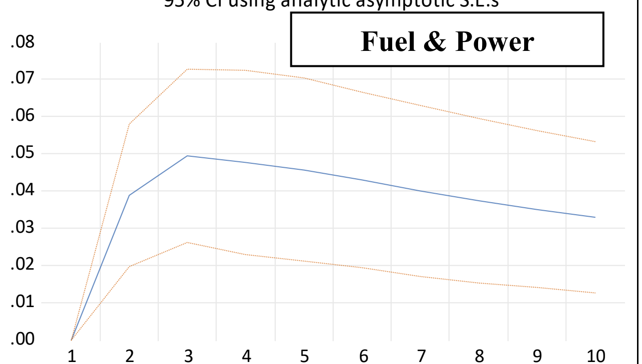
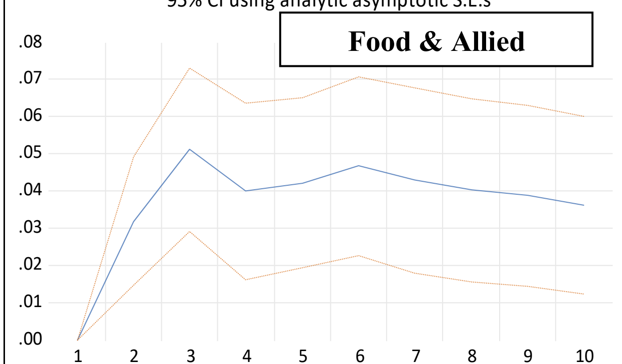


Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s



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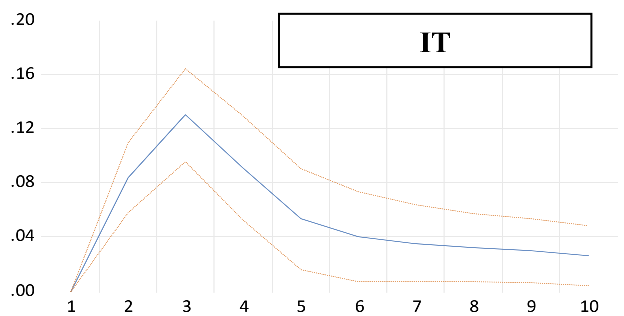

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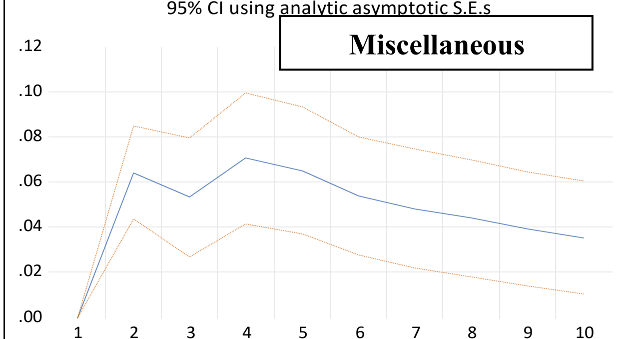
95% CI using analytic asymptotic S.E.s



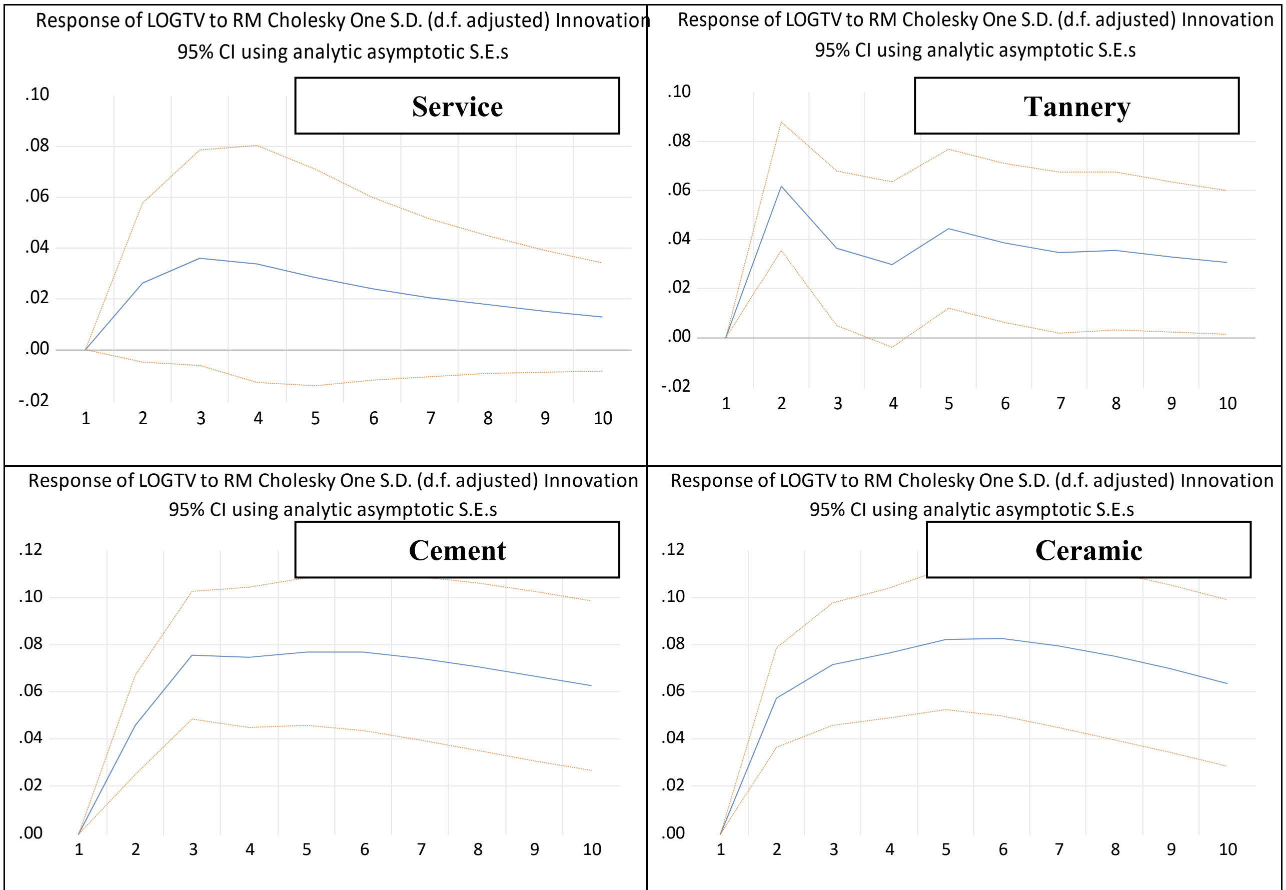
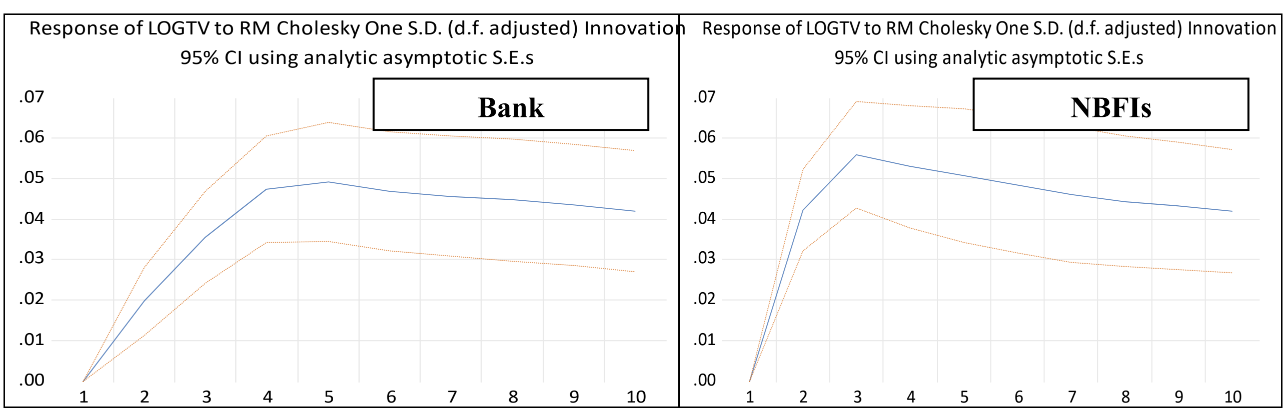
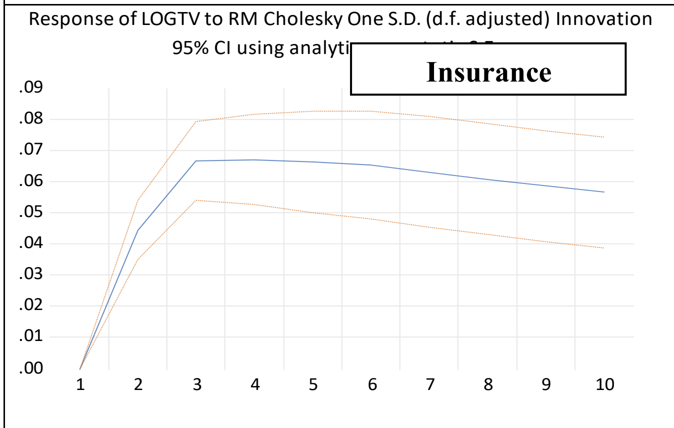


Figure 5.12: Impulse Response of Trading Volume to Market Returns for the Crisis Market

Table 5.25: Empirical Results from VAR model for the Extended Crisis Market							
	Bank	NB	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.907***	0.707***	0.687***	0.800***	0.660***	0.793***	0.762***
TV(-2)	-0.057	0.082	0.046	0.002***	0.051	0.563	-0.025
TV(-3)	0.107***	0.163***	0.197***	0.110	0.172***	0.078	0.210***
$R_m(-1)$	0.010***	0.020***	0.027***	0.006***	0.009***	0.021***	0.013***
$R_m(-2)$	0.004	0.003	0.007***	0.007***	0.007	0.003	0.005
$R_m(-3)$	0.006***	-0.000	0.000	0.008***	0.004	-0.003	0.004
Constant	0.402***	0.416***	0.598***	0.722	0.994***	0.599***	0.448***
CSAD	0.001	-0.000	0.008***	0.000	0.002	0.003	0.004
CSAD(-1)	-0.003	0.004	-0.008	0.003	-0.004	0.007***	o.003
CSAD(-2)	0.005	-0.000	-0.001	0.001	-0.003	-0.002	0.001
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.600***	0.675***	0.624***	0.891***	0.551***	0.666***	0.599***
TV(-2)	0.050	-0.057	0.083	-0.074	0.194***	0.100	0.156***
TV(-3)	0.025***	0.231***	0.153***	0.078	0.177***	0.176***	0.132***
$R_m(-1)$	0.023***	0.027***	0.029***	0.000	0.017***	0.012***	0.016***
$R_m(-2)$	0.018***	0.017***	0.007	0.001	0.002	0.017***	0.017***
$R_m(-3)$	0.001	0.001	0.012***	0.003	0.003	-0.007	0.002
Constant	0.800***	1.113***	1.081***	0.808***	0.551***	0.470***	0.898***
CSAD	0.022	0.023	0.036***	0.003	0.001***	0.019***	0.021***
CSAD(-1)	-0.007***	0.002	-0.037	0.002	0.010	-0.006	-0.010***
CSAD(-2)	-0.019	-0.025	-0.004	-0.001	0.000	-0.018	-0.005

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level
*Significant at the 10% level.
Source: Author's Own Calculation.




Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
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Insurance
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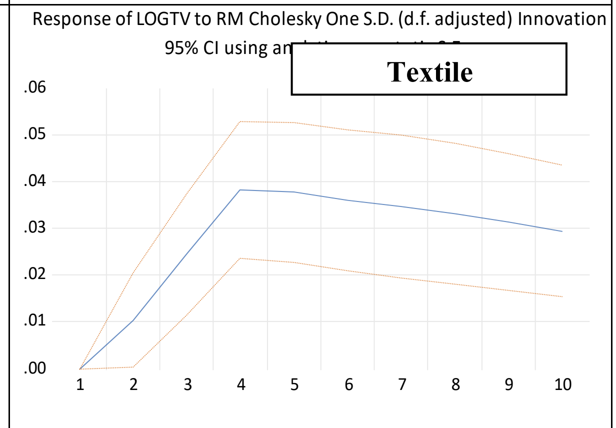
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
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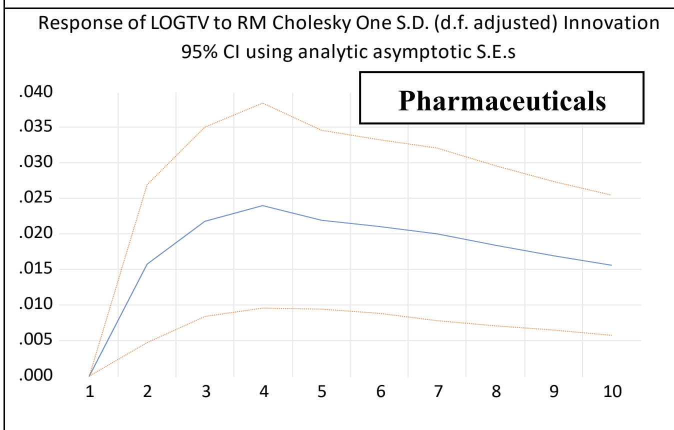
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Pharmaceuticals
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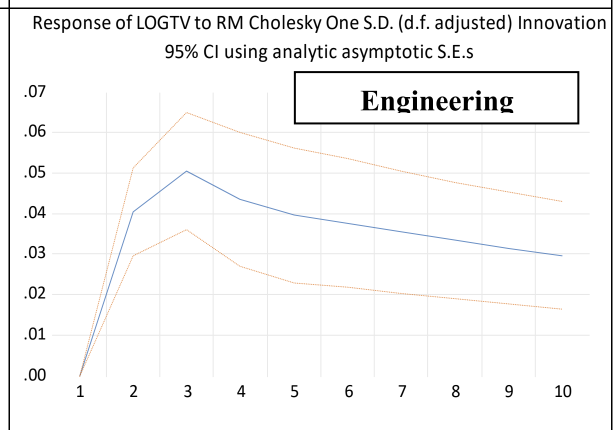
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
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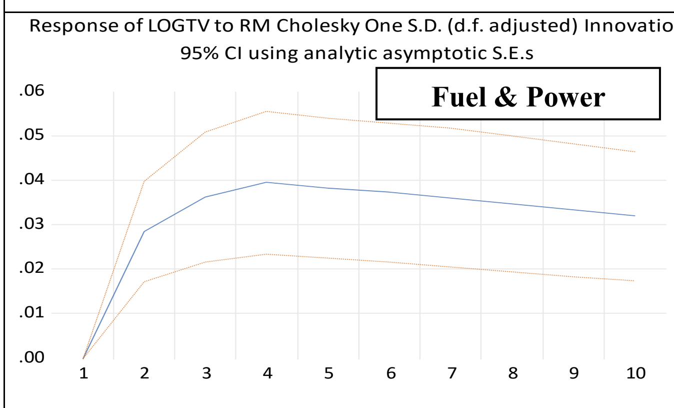
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
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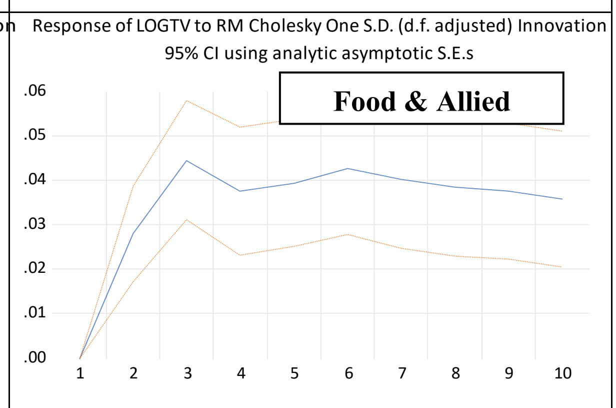
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
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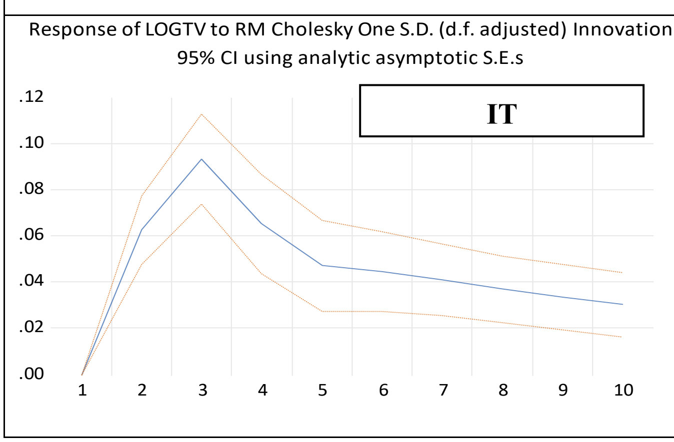
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
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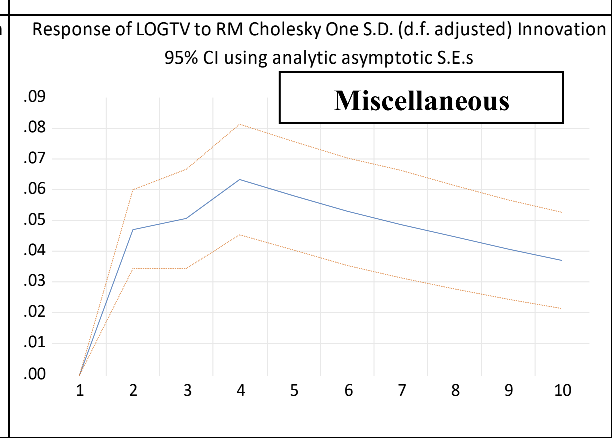
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
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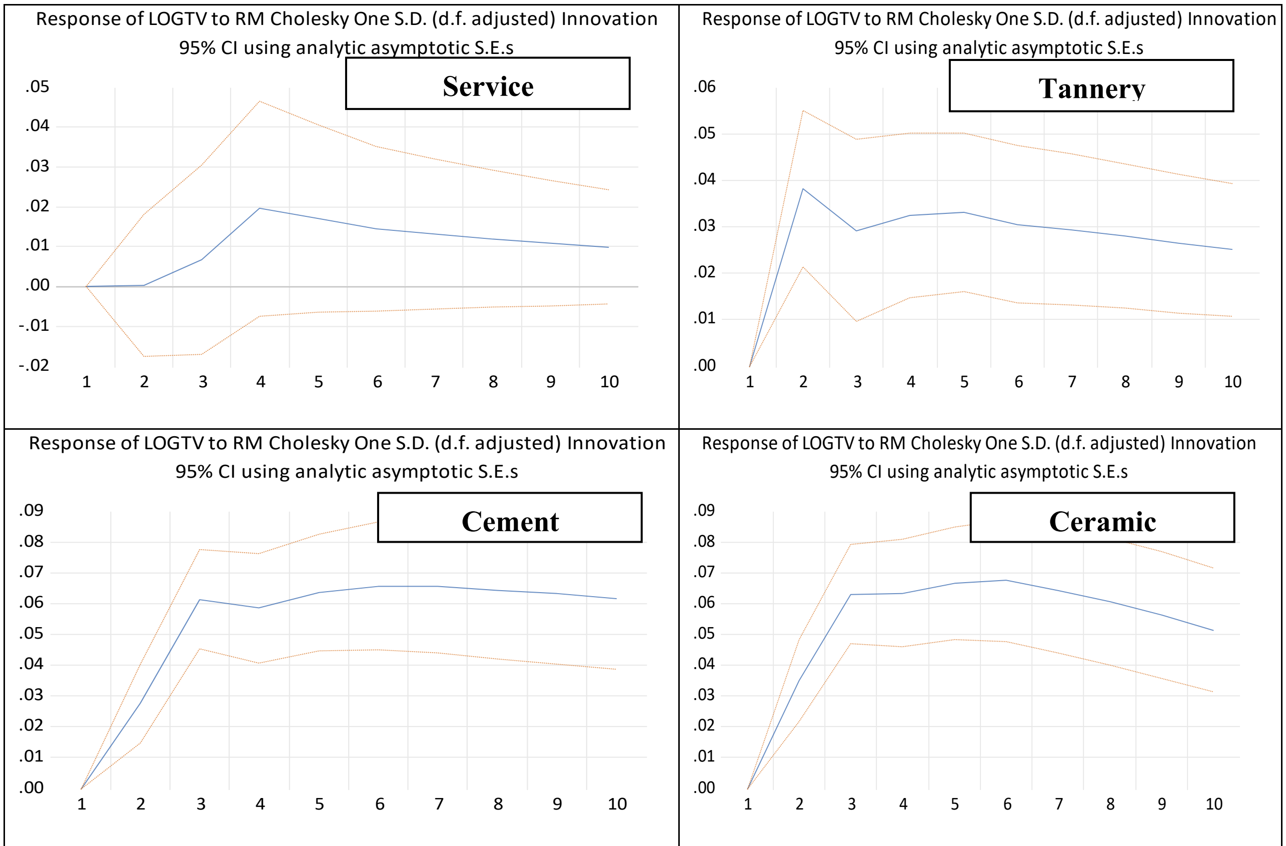


Figure 5.13: Impulse Response of Trading Volume to Market Returns for the Extended Crisis Market

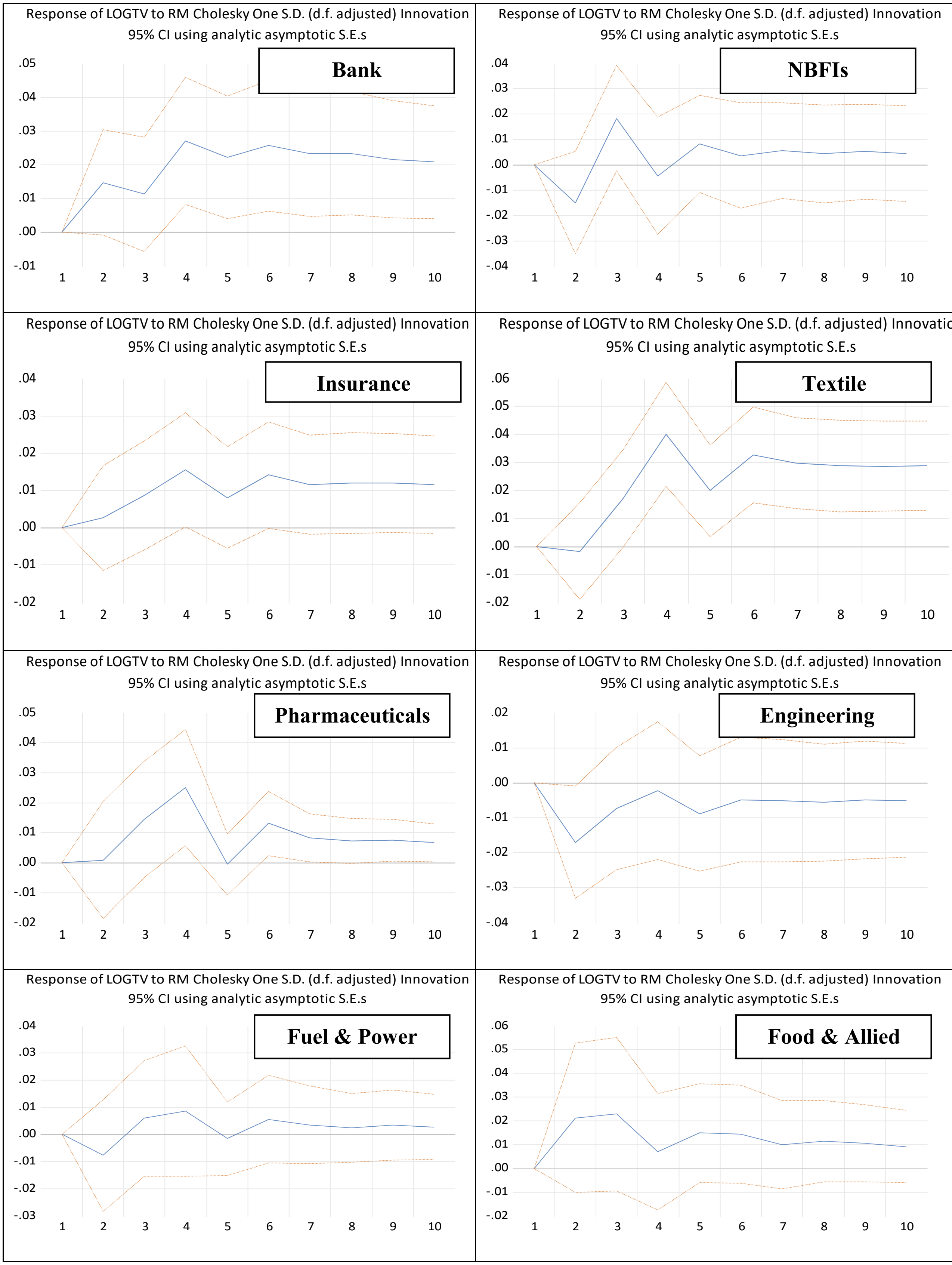
As a result of COVID-19 pandemic, financial markets worldwide experienced unprecedented level of uncertainty, resulting in increased market volatility, rapid correction in the market, and shifts in the sentiment of investors. In contrast to the findings in other market states (Overall, bearish, bullish, crisis, and extended crisis), the COVID-19 market presents a stark contrast, where overconfidence bias is almost nonexistent at the industry level except for Pharmaceuticals and Textile. This suggests that investors more cautiously reacted to pandemic related uncertainties and relied on fundamental indicators rather than technical patterns of past prices. The COVID-19 pandemic was an exogenous, global shock to equity market, forcing investors to abandon past return-based trading strategies and reacting to government interventions and other economic disruptions. Unlike speculative trading initiated in bullish or crises markets, investors during the pandemic might have favored liquidity management, capital preservation, and defensive trading strategies instead of developing overconfidence-driven trading behavior.

Though overconfidence bias was largely absent in all industries during global crisis, Textile and Pharmaceuticals industries evidenced signs of this behavioral trait. These two industries explored pandemic related growth potential including the demand for personal protective equipment (PPE), vaccine developments, medical supply chains, rising healthcare spending, supply chain adjustments, and changing export policies, prompting investors to make trading decisions with an overabundance of confidence. The COVID-19 provides an extremely uncertain market environment, which significantly alters investor psychology. This behavior aligns with the theory of the Adaptive Market Hypothesis (AMH), where investors tend to adapt their behavior in response to changing market conditions. The findings also reiterate the crisis-induced risk aversion behavior of investors in the Bangladesh equity market. While overconfidence was present in crisis market (where market experienced a massive crash), the COVID-19 pandemic was different in that it brought completely new systemic global shocks, rendering previous industry returns less relevant.

Table 5.26: Empirical Results from VAR model for the COVID-19 Market

	Bank	NB	Insurance	Textile	Pharma	Engineering	Fuel & Power
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.477***	0.325***	0.433	0.389***	0.145***	0.509***	0.247***
TV(-2)	0.255***	0.366***	0.333	0.250***	0.313***	0.311***	0.399***
TV(-3)	0.173***	0.282***	0.204	0.322***	0.349***	0.139***	0.265***
$R_m(-1)$	0.020	-0.011	0.002	-0.001	0.000	-0.016	-0.005
$R_m(-2)$	0.001	0.016**	0.007	0.016***	0.011	-0.001	0.004
$R_m(-3)$	0.017	0.002	0.012	0.033***	0.020***	0.008	0.008
Constant	0.840***	0.210	0.247	0.372***	1.705***	0.364***	0.749***
CSAD	-0.002	0.018***	0.001	0.011	-0.005	-0.005	0.009
CSAD(-1)	-0.015	-0.010	0.002	-0.020	0.007	-0.011	-0.005
CSAD(-2)	0.007	-0.000	-0.006	-0.000	0.002	0.007	0.003
	Food & Allied	IT	Miscellaneous	Service	Tannery	Cement	Ceramic
	TV	TV	TV	TV	TV	TV	TV
TV(-1)	0.250***	0.302***	0.288***	0.442***	0.217***	0.249***	0.510***
TV(-2)	0.266***	0.424***	0.403***	0.179***	0.370***	0.308***	0.121***
TV(-3)	0.351***	0.219***	0.273***	0.305***	0.260***	0.301***	0.289***
$R_m(-1)$	0.016	0.009	0.005	0.006	0.012	0.021	-0.000
$R_m(-2)$	0.012	0.008	0.003	-0.006	0.001	0.024	-0.017
$R_m(-3)$	-0.004	-0.002	0.004	0.019**	-0.003	-0.011	-0.005
Constant	1.039	0.402***	0.644***	0.541***	1.061***	1.172***	0.572***
CSAD	-0.002	-0.002	-0.006	0.028	0.031	0.000	0.007
CSAD(-1)	-0.004	-0.001	-0.007	-0.015	0.018	0.017	0.013
CSAD(-2)	0.009	0.005	-0.005	-0.014	-0.005	-0.038	-0.002

Notes: TV denotes the log of equally weighted market trading volume, R_m denotes equally weighted market return, CSAD is the cross-sectional absolute deviation, and Volatility presents the variance of market return.
*** Significant at the 1% level
*Significant at the 10% level.
Source: Author's Own Calculation.


Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Bank
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
NBFIs
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Insurance
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Textile
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Pharmaceuticals
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Engineering
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Fuel & Power
Response of LOGTV to RM Cholesky One S.D. (d.f. adjusted) Innovation
95% CI using analytic asymptotic S.E.s
Food & Allied

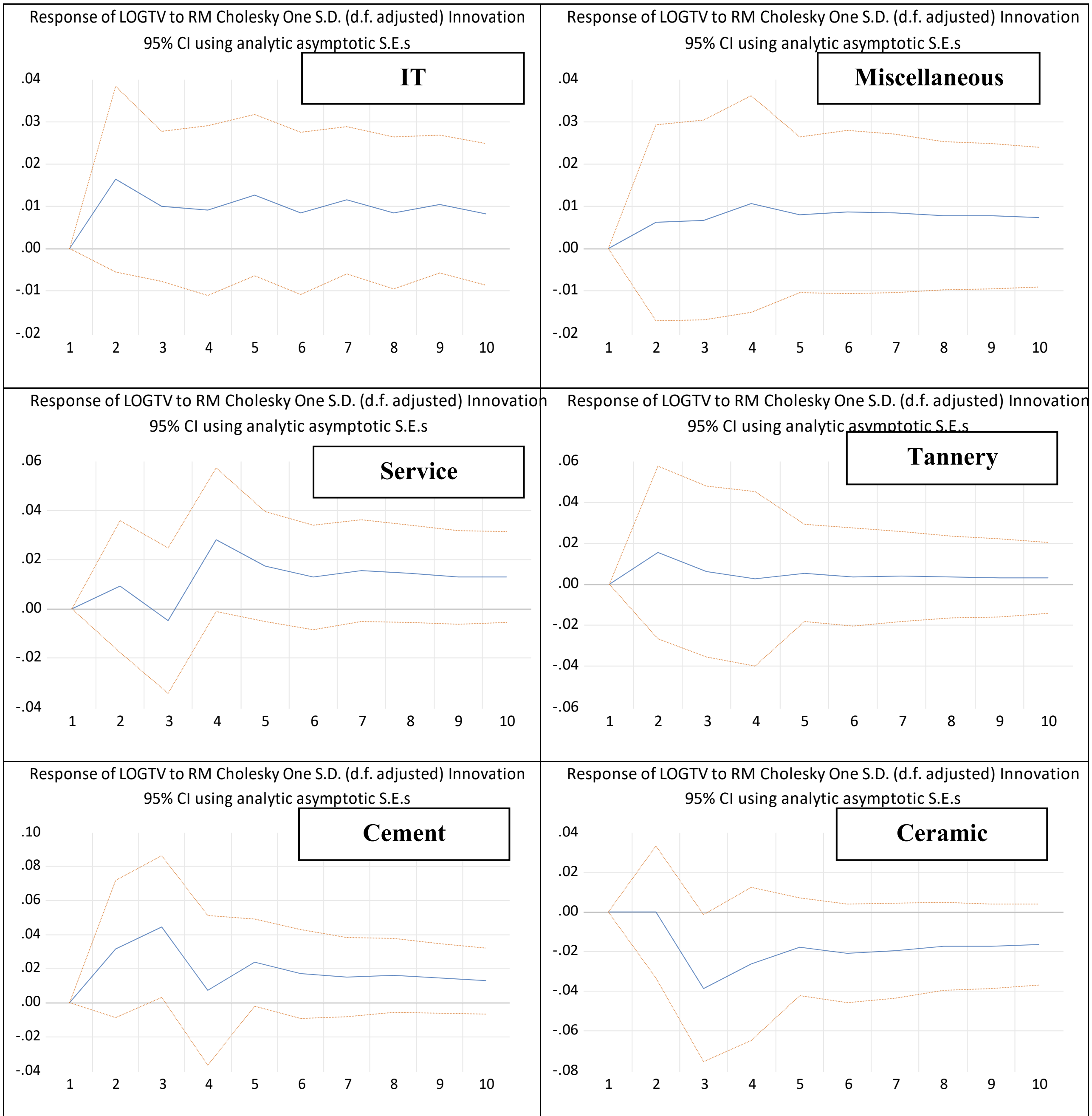


Figure 5.14: Impulse Response of Trading Volume to Market Returns for the COVID-19 Market

Overconfidence bias within bullish and bearish market phases, classified applying Dow Theory, provides a deeper understanding of how investors psychology varies with industry trends. The findings largely mirror those of the overall market, which reaffirms the presence of overconfidence bias across most industries except Tannery. Overconfidence bias is more pronounced in bearish market than in bullish, consistent with the behavioral finance theory that loss aversion may encourage investors to trade more aggressively in an attempt to recover losses by relying on past industry return patterns (Kahneman & Tversky, 1979).

The findings for the crisis and extended crisis markets reveal that, although overconfidence bias remains apparent in most industries except Service and Tannery, it is less pronounced as no industry shows significance in all three lag periods. The result aligns with behavioral theory, contending that extreme market downturns may distort cognitive biases and cause investors to behave more cautiously.

COVID-19 exhibits a distinctive deviation from the other market states, with overconfidence bias primarily absent in all industries except for Textile and Pharmaceuticals industries. Unlike any other financial crisis, COVID-19 shock was unpredictable, unprecedented, impacted more than just economic factors to societal disruption. Therefore, investors struggle to rely on past industry return patterns as the new market dynamics emerged without historical precedent, which greatly reduced overconfidence-driven trading behavior. Despite the absence of overconfidence during the COVID-19 period, Textile and Pharmaceuticals industries exhibited persistent investor overconfident behavior that can be linked to high investor attention and industry-specific characteristics. During this global crisis, investors redirected their focus toward these industries recognizing their crucial role in pandemic response, healthcare demand, vaccine production, government's financial incentives and policy attention to support these industries likely reinforced speculative excessive trading activity.

5.8.11 Limitations of Direction of Causality and Feedback

Empirical evidence of the VAR, Transfer Entropy, and the LSTM model demonstrate that the past market returns are important predictors of trading volume (a major indicator of overconfidence) but one must not ignore the reciprocal relationship between the returns and the trading volume. Trading in dynamic markets can affect future price dynamics because of liquidity shocks, information revelation and amplification of market sentiment. Although the VAR model has the benefit of taking into account lagged interdependence and Transfer Entropy gives directionality in the flow of information, these models are not able to completely remove the structural causality of feedback that may be present in high-frequency data.

Thus, the results were to be used as the indication of the predictive power but not the actual causation. The lead-lag pattern may be explained by behavioral theories -past experience leads investors to be confident and thus stimulates more trading, but future studies can expand this analysis with structural vector autoregression (SVAR) or Granger-causality analysis with an endogenous model in order to further decompose behavioral causality into market mechanics. This elucidation makes sure that behavioral interpretations remain practical in both statistical and behavioral theories.

5.9 Conclusion

Overconfidence bias suggests that investors overestimate their knowledge and ability to predict future equity market movements. This bias is manifested in the equity market through excessive trading activities in response to past market return behavior. Overconfidence bias is empirically validated by the hypothesis that market return can impact trading volume, with past returns bolstering investors' belief in their predictive expertise**.**

This essay investigates overconfidence bias by applying three dynamic methodological applications such as vector autoregressive (VAR), transfer entropy and machine learning model across diverse market states including bearish, bullish, crisis, extended crisis, and COVID-19 in the Bangladesh equity market. Existing studies focus on whether total market returns can predict trading volume, a sign of overconfidence bias in the financial market. This research shifts the perspective from total market returns to the unexpected market returns to isolate the surprise or unanticipated component of returns, which better reflects the essence of investors' overconfidence.

The essay examines overconfidence bias using both the total and the unexpected market returns employing all three empirical methodologies.

The findings from linear VAR model reveal that overconfidence is a persistent behavioral phenomenon among investors in the Bangladesh equity market in most market states under both the total market returns and the unexpected market returns. This overconfident behavior is also confirmed in asymmetric market conditions, which demonstrate that investors not only overreact to market returns during the specific market phases but also reinforce the robustness of the findings. Transfer entropy further provides the dynamics of overconfidence by evidencing its presence in the whole market along with bullish and COVID-19 market states. This state-dependent variation of the findings discovered by the non-linear transfer entropy underscore its practical applications in exploring overconfidence behavioral patterns that traditional VAR night fail.

The essay also investigates overconfidence bias applying Long Short-Term Memory (LSTM)- a deep machine learning approach designed to analyze complex temporal relationships in time-series data. Results suggest that both the total and the unexpected market returns have predictive power over trading volume in the whole market as well as in bearish, crisis and extended crisis markets. It implies that LSTM utilizes its memory architecture, developing delayed and long-term behavioral patterns in investor psychology, especially in crisis-driven equity market conditions.

In all three models, the overall market exhibits this predictive relationship, which illustrates the robustness of the results.

The essay findings uncover a new insight into overconfidence, what we call ***defensive overconfidence*.** As opposed to conventional overconfidence, which typically occurs during rising markets, *defensive overconfidence* occurs when markets are downturns or crisis driven. The insight extends behavioral finance theory by illustrating that overconfidence is not only an expression of optimism, but also a psychological defense mechanism observed under market stress. It adds a new dimension to behavioral finance literature, offering a stronger and state-contingent market understanding of how investors' psychology evolves across market states. This opens up a new avenue for overconfidence study, particularly in emerging and frontier equity markets. Strikingly, the results of the LSTM indicate that investors react more strongly to unanticipated market movements, indicating that overconfidence is persistent as well as context dependent. As a result of this insight, it becomes increasingly important to consider market states and surprise elements when evaluating behavioral biases across frontier markets.

Defensive overconfidence has numerous economic implications to the frontier markets like Bangladesh. Excessive confidence of investors regarding predictive power causes the overtrading, misallocation of liquidities, and temporary burst of volatility in the stock markets during the times of downturns or crisis conditions. Rather than retreating into the market and experiencing doubts, overconfident traders are now going to keep trading aggressively, hoping that they can reverse over time or take advantage of a mispricing. This can cause some interim liquidity due to this sustained trading pressure, but it tends to destabilize market equilibrium by increasing price volatility and decoupling of prices and fundamentals.

Moreover, *defensive overconfidence* may cause a distortion in pricing risks and hinder recovery in the market. Investors boosting speculative trading and increasing leverage exposure when they collectively overrate their forecasting skills in predicting rebounds are helping to create post-crisis volatility persistence. To regulators and policymakers, it is essential to be aware of defensive overconfidence because it suggests that conventional stabilizing mechanisms, such as margin requirements or trading halt, might not be very effective when psychological drivers continue trading momentum even when markets are falling. Therefore, the insights into this behavior can inform the development of the behavior-sensitive market stabilization and investor education interventions depending on frontier markets conditions.

In addition to aggregated market-level analysis, the essay also investigates the overconfidence bias at the industry level in the Bangladesh equity market. The findings reveal that overconfidence bias persists in almost all industries across diverse market states except for COVID-19 market. This study makes an important contribution to the behavioral finance literature by examining a comprehensive view of how investors overconfident behavior at the industry level manifest across different market states such as bearish, bullish, crisis, extended crisis, and COVID-19 markets within a frontier equity market.

Chapter Six- Herding Behavior: An Examination in Frontier Equity Market and The Impact of Macroeconomic Shocks and Monetary Policy Shifts on Herding Dynamics

6.1 Background of the Study

The dynamics of the investment behavior of equity market participants has always been a puzzling issue to academic reserachers, and practitioners. Academic research on behavioral finance has devoted significant efforts to understand these behaviors and its ensuring impact on equity market prices. Traditional finance is built on the assumption of rationality framework where investments are processed with the help of its inherent theories like Markowitz portfolio theory, the capital asset pricing theory (CAPM) of Share and Linter, and the efficient market hypothesis (EMH) of Eugene Fama.

According to Barberies et al., (2006), rationality defines in two perspectives. The first perspective is investors update the new information upon its arrival and resuffle their beliefs in the upgraded manner as specified by Bayes Law. The second perspective states that investors have the motivation to make choices subjectively desirable according to the principles of expected utility function. Market participants judge their investment decisions with the objectives of maximizing self-interest and are influenced by any form of fear, regret, or state of human psychology exposed to their beliefs. They resort to the investment decisions based on information perceived to be good enough to estiamte the risk-return charateristics of the securities in question and finally make their investment decisions.

Classical view of finance is dominantly centered on the efficient market hypothesis (EMH) which presumes that economic agents are rational and involve in arbitrage opportunities to exploit any discrepancy happening between securities fundamental values and market prices by simply buying the undervalued and selling the overvalued stocks. This smart strategy will help investors restore equilibrium in the market. Efficient market hypothesis (EMH) relies on the assumption that security prices reflect all available information, and it is impossible on the part of investors to consistently outperform the market.

There could be the patterns or phenomena observed in the security prices which may arise due to systematic errors or irrational behaviors of equity market participants. The presence of these anomalies challenges the notion of EMH theory and suggests that economic agents do not always behave rationally. These irrational behaviors can lead to distortion in security prices that may persist over time. Understanding these anomalies necessitates the importance of behavioral finance in explaining market phenomena that account for human biases and irrational behaviors of investors.

Behavioral finance has emerged a new area of finance to understand the nature of human psychological charateristics such as emotions, perceptions, thinking attitudes, philosophy about risk absorption preferences, social aspects, and many other cognitive issues. According to the traditional finance, these issues are not deemed to be relevant in investors' decision-making framework. Thus investors' judgment about the securities fair value and their corresponding decisions to buy, or sell or hold a particular stock are subconsciously affectcted by the aspects of various psychological cognitive biases namely herding behavior, overconfidence, disposition effects, cognitive dissonance, loss aversion, conservatism, representativeness etc.

Herding behavior is one of the fundamental biases in behavioral finance that exists in the context of equity market to ascertain the psychological motivation of the market participants. Market prticipants have inherent psychological characteristics to follow others in their investment decisions (De Bondt et al., 2008). Bikhchandani & Sharma (2000) define this imitating behavior as a situation when investors hold back thier independent information and tend to follow the observed market behavior. The presence of herding behavior in the equity markets represents the violation of rational utility maximizing finance theory (Lao & Singh, 2011) and this behavior of investors may produce the increased equity market volatiltiy and destabilize the financial markets (Venezia et al., 2011; Demirer & Kutan, 2006). Herding in behavioral finance can be described as emotional tendency of the equity market investors to copy the decisions of others overlooking their own knowledge/capacities (Vieira & Pereira, 2015; Li et al., 2018). Empirical studies manifest that presence of herding behavior in the equity market may have crucial effects on securities fair prices and can significantly impact the risk-return characteristics of securites (Tan et al., 2008). The behavior of market participants to herd may induce to destabilize the equity market reflecting the possibilities to bring, or to some extent, contribute to market crasehs or bubbles (Scharfstein & Stein, 1990; Shiller, 1990).

In real investment situation, equity market participants exhibit the irrational behaviors that may be due to distortions in their thinking process, or having the execution of the efforts of psychological issues possess in their brain. This unorthodox decisions made by them are deviated from the pattern of rationality based decisions observed in the traditional finance thoery.

Dhaka Stock Exchange (DSE) is the premier bourse in Bangladesh and was established in 1954, although its formal trading started in 1956. The DSE is regulated by the Bangladesh Securities and Exchange Commission (BSEC) and has diverse range of companies listed across 22 various sectors. The DSE has three indices to track the performances of listed securities are DSEX (is the benchmark market index), DS30 (is the index constructed with 30 leading trading companies), and DSES (is the Shariah-based index). MSCI (Morgan Stanley Capital International) classified the global equity market into developed, emerging, and frontier equity markets on the basis of three criteria: economic development, size and liquidity of the equity market and accessibility of foreign investors.

Developed equity market is defined as highly developed economies and financial markets. Emerging equity markets are the countries with rapidly growing economies and developing financial markets. Whereas the Fortier equity market is classified as the countries with less developed financial markets having lower liquidity and higher risk.

6.2 Research Problem

Investigation of herding behavior enables investors, researchers and other market participants to understand about the level of equity market efficiency. The evidence of herding behavior may prove price and information inefficiency (Yao et al., 2014). Its existence suggests that security market prices are distorted from fair values due to the influence of investors' psychological factors rather than reflecting their fundamentals. This challenges the notion of efficient market hypothesis (EMH) and signifies the arbitrage opportunities or any kind of investment strategy that exploit securities mispricing (Lao & Singh, 2011). Examining herding behavior is also crucial to understand the dynamics of price movements in the equity market. For example, existence of herding behavior can provide an insight into the pattern of buying-selling behavior of investors that drive short-run market fluctuations. This information is valuable for investors to anticipate the market trends and develop the potential risk-return payoffs. This research on herding behavior can shed light on the underlying forces of market movements and the factors that influence investors' sentiment, emotions, and other psychological traits.

The phenomenon of herding behavior is still a new avenue for research for Bangladesh equity market, characterized by small market capitalization, low liquidity, high risk, limited participation of foreign investors, poor regulatory framework, lack of transparency in trading procedures, weak corporate governance compliance, and more vulnerable to political tensions. All these issues reflect the inefficiency of Dhaka stock exchange which has also been supported by the empirical studies of (Alam et al., 2017; Mobarek et al. 2008; Arefin & Rahman, 2011; Shiblu & Ahmed, 2015). The inefficient market representation always increases the probability of detecting herding behavior among investors in the context of a frontier equity market like Bangladesh. Despite extensive research in the existing literature, very limited studies have investigated how herding behavior manifests under different market states in Bangladesh. The lack of a structured framework to quantify herding across these market states exacerbates market stability and regulatory intervention concerns. Addressing this gap, the study focuses on systematically investigating market-wide herding behavior in frontier equity market like Bangladesh across diverse market states, including bearish, bullish, crisis, extended crisis, and COVID-19 markets.

6.3 Contributions of Research

This research contributes to existing literature in the following ways. First, there are only two studies carried out on herding behavior in Bangladesh equity market. The first study was conducted by Ahsan & Sarkar (2013) for the period 2005-2011 and the second study was done by Khan & Imam (2023) examining herding behavior in equity prices of 160 companies for the period 2007-2011. The data set used by both studies is confined to a relatively small set of observations and included a few companies. Our research contains a large data set spanning from 2012-2021 on all companies listed on Dhaka Stock Exchange (DSE).

Second, all previous empirical research on herding behavior has classified the equity market as a bullish one when the market return is positive on a day, and a bearish market when the return is negative. Our research makes a remarkable contribution to the existing herding literature in the equity market by introducing an innovative approach to determining bullish and bearish market phases based on the principles of the Dow Theory. No single prior research on herding behavior all over the world has applied the Dow Theory framework to segregate bullish and bearish markets. Therefore, this distinct market classification extends a fresh methodological development to understand the dynamics of investors' behavior during different market conditions.

Third, Prior empirical research has predominantly examined asymmetric pattern in herding behavior conditioned on market directions, high or low trading volume, and high or low market volatility in the context of entire market period. Our research makes a significant contribution to literature by delineating asymmetric herding patterns within each market classification developed in this research such as bullish, bearish, crisis, extended crisis, and COVID-19 markets, which may provide valuable insights into the differential dynamics of investment behavior of market participants across these markets.

Fourth, the majority of empirical studies primarily focus on market-wide herding behavior across global equity markets. The thesis further investigates herding behavior at the industry-level to uncover how investors' herding tendencies manifest differently across various industries.

Fifth, the study offers a unique advancement to existing literature by examining the impact of both macroeconomic shocks and monetary policy shifts on herding dynamics. This unexplored empirical evidence from Bangladesh equity market bridges behavioral finance and macro-financial dynamics, even across diverse market states.

Sixth, the thesis also investigates herding behavior by employing quantile regression particularly in frontier equity markets setting. This methodological development provides insights into how herding intensity may vary under different distributions of market returns and within the diverse market states.

6.4 Theoretical Framework

To understand the complexities of investor behavior has significant implications for dynamic sphere of the equity market. Herding behavior is one of phenomenon observed in market dynamics, which stands out as a significant element shaping the market movements. The theory of herding behavior was popularized in the 1990s with the pioneering research of Banerjee (1992) and Bikhchandani et al. (1992). In the context of behavioral finance literature, herding behavior is the representation to delineate the correlations in trade arising out of interactions among the equity market participants (Chiang & Zheng, 2010). Theoretical framework sheds light on how investors may follow the actions of others under the assumption that others possess valuable relevant information (Bikchandani et al. 2005); Avery & Zemsky (1998), Park & Sabourian (2011). This section will unfold the phenomenon of herding behavior as a foundational structure on which subsequent empirical analysis is to be conducted. we will present the theories of herding to perceive how the behavior of investors are modeled and to investigate the the possible causes of this phenomenon.

The herding propensity of the investors in the equity markets can be categorized into two broad motivational theories: unintentional herding (spurious herding) and intentional herding (Bikhchandani & Sharma, 2000). Devenow & Welch (1996) explan that market participants believe they can access to favorable outcomes by intentionally following the behavior of others assuming that others information is superior to their own (Economou, 2020).

Meaning of Herding

There aremultiple variations on which the concept of herding can be defined seemed to be quite similar in essence but encapsulate different herding testimony.

In its simple form, herding can be defined as the imitation of what others are doing forsaking their own analysis about the concerned investment vehicles. It is presumed that investors having lack of knowledge about a particular investment may try to stick with others decisions believing that others have superior information regarding the risk-returns charateristics of that investment. Investors tend to conform to the decisions of others because of the level of sophistications of the securities or the lack of ability of the characteristics of the equity markets.

Hwang & Salmon (2004) defined herding as "imitating the behaviors of other investors or movements of the financial markets rather than copying own information packages".

Lakonishok et al.(1992) defined herding behavior "as the average wilingness of the group of investors to buy and sell the particular stock simultaneously".

Nofsinger & Sias (1999) terms herding " a group of market participants who base their trading decisions in the same direction during the same period".

According to Aversy & Zemsky (1998), " herding means investors who sacrifice their initial assessment and do trade by looking at the trend in previous trade".

Hirshleifer & Teoh (2003) interestingly defined "herding as the kind of behavior finally converge to average".

"Herding is a form of correlated behavior" (Hwang & Salmon, 2004).

Herding refers to "a group of investors following each other into (out of) of the same securities" (Sias, 2004).

In psychology, the imitating behavior is commonly treated as the nature of human beings. The implied mimicking tendency of human beings is the outcome of interactive communication either explicitly through talking to each other directly or tacitly through observations.

6.4.1 Intentional Herding

Intentional herding refers to the situation when investors follow the other investors decisions purposefully disregarding their own initial information. According to this form of herding, market participants herd sacrificing the available information they possess and decide to duplicate the behaviors of other players simply to earn the similar returns with them (Caparreli, Arcaugelis & Cassuto, 2004). Intentional herding seems to be sentiment-driven and presumes that market participants have the dearth of reliable information about the investment decisions. Therefore, they follow the strategy that go along with mass participants.

Intentional herding caln also be categorized into rational herding and irrational herding. This classification of herding is developed on the bassis of rationale behind herding by investors (Devenow & Welch, 1996; Christie & Huang, 1995). Rational herding can be described as situation when the intention of the equity market participants is to execute the investment behaviors of others overlooking their own information believing that others possess the better information than themselves. In rational herding, investors believe that they may not have perfect knowledge regarding actual equity market conditions to make effective investment decisions, and they tend to rely more information on market consensus to imitate them (Baddeley et al., 2012).

By contrast, irrational or noninformation-based herding incurs when investors unconditionally (blindly) replicate the behaviors of other market agents or participants ignoring their own beliefs about the matket (Banerjee, 1992; Bikhchandani et al., 2005). This kind of behavior occurs as a result of psychological stimuli and pressure from social groups or social habits (Spyrou, 2013).This herding behavior may force the securities prices away from the fundamental values and represent the securities mispricing in the markets (Hirsleifer et al., 1994; Hwang & Salmon, 2004; Hung et al., 2015).

The Explanations of Rational Herding Behavior

The three most plausible motivations regarding rational herding behavior in the equity markets can be described from behavioral literature are: Information cascade, reputation and compensation motivations (Bikhchandani & Sharma, 2000).

Information Cascade

Information cascade can also be termed as imperfect information. It can be defined as a phenomenon in behavioral economics where investors make the similar decisions under uncertainty based on what they regard to be public information neglecting their own private knowledge. Under this concept, decisions are usually made sequentially on the condition that preceeding decisions are public information. Investors believe they possess lack of knowledge on their capabiliites to process relevant information to make actual investment decisions force them to follow the others, even it may not be rational to do so (Bikhchandani & Sharma, 2000).

Bickchandani, Hirshleifer, & Welch (2005) defines information cascade "as a sequence of decision making by economic agents given that it will be optimum for them to ignore their own private information and imitate the behavior of agents ahead of them". Under information cascade model, market traders simply follow the investment behaviors of other market players because they perceive (observed from others trading behavior)other trades possess the relevant information (Bickchandani, Hirshleifer, and Welch, 2005; Banerjee, 1992; and Avery & Zemsky, 1998).

We explain with an example to describe how information cascade works through the demonstration of sequential decisions. No verbal interaction can be apprehended in information cascade process. Assume that there are five investors: A, B, C, D, and E. They have only two choices: Accept or reject.

A is the first investor who makes decision solely based on his personal information and he accepts the decision. B is the second decision maker and possesses the public information about investor A who already made the decision to accept. B continues with decision of A. This decision may be based on both private and public information. Now, C, the third investor, disregard his own knowledge that ensures rejecting and accepts the decision because previous two investors (A,B) already had the same decision. In this stage cascade starts. Because any individual investment action does not constitute his/her private information. C is obviously duplicating the others decision. D figures out the choices of A, B, and C. He also accepts the decision by imitating them. In this way, E also ignores his own private information and joins with them. E has now strong belief about the decision choice to accept because public information pool is intensified with the involevement of all four predecessors.

One of the intrigue charateristics of information cascade is that once a cascade process starts, the private information that the subsequent investors possess can never be incorporated in the public pool of knowledge.

Reputation Motivation

Reputation-based herding introduced by Scharfstein & Stein (1990) arguably pointed out that investment professionals like mutual fund managers, pension fund managers or other institutional investors impliedly prone to herd because of uncertainty about their ability to make correct decisions. Reputation cost may lead to herding behavior,because the asymmetric information on ability and reputational concern may force managers to persue the decision of others (Scharfstein & Stein, 1990; Hong et al., 2020). Managers will have the predisposition to mimic the investment decisions of other mangers(peers) by abandoning their substantive private information to avoid the negative consequences of underperformance on their reputation. The reputation herding behavior is the outcome of conservatism motivation displayed by the investment managers in their decision process and the slow absorption framework of any new innovation taken place in the market environment (Zwiebel, 1995). It is argued that most of the managers become less confident in executing their decisions which are deviated from market standard, the benchmark performances produced by other reputed mangers in the similar profession.

The managers imitating behavior can be supported from two types of motivations: career pressure and peer pressure. In the firest case, managers herd because they are concerned about their positions in the labor market to assess how others will appraise their capacity on decision making efficiency. In case of peer pressure motivation, it is believed that risk taking behavior of managers is influenced by others' risk taking behavior in their peer forum (Graham, 1999). Therefore, mimicking strategy for the managers can lead to positive reputation externalities arising from the actions among the peer group.

Compensation Motivation

If the compensation schemes offered to the managers are tied to the benchmark performances of other similar professionals, then managers will have the intuitive tendency to herd (Maug & Naik, 1996). Professional managers do have the incentives to replicate the other managers' actions to preserve the compensation packages. For example, a manager's compensation scheme depends predominantly on how well his performance matches the benchmark performance of other manager in the similar profession. The investment managers are presumed to be motivated for achieving a level of income that reassure their benchmark performances. The managers always remain concerned about any level of underperformances because it could adversely affect their income level and intend to imitate the other managers decisions to insulate themselves from earning lower income. The motivation of compensational herding is that managers expect to perform in line with industry benchmark but especially not inferior (Spyrou, 2013).

6.4.2 Unintentional or Spurious Herding

Unintentional herding occurs fortuitiously in a situation when all market participants have the homogeneity of information and deal the similar decision problems. This behavior exists because investors are allured with same kind of stock characteristics like high retrun, high liquidity (Falkenstein, 1994) or they evaluate the common market factors and get the correlated private information to make a homogeneous decisions regarding an individual investment (Hirshleifer,Subrahmanyam & Titman, 1994).

This form of spurious herding comes to light due to changes in financial fundamentals. Suppose, investors in the equity market will simultaneously go for the selling of highly leveraged securities in response to an abrupt increase in interest rates in economy. Under this circumstance, investmets, in general, will become less attractive and there will be tendency on the part of investors to withdraw their investments from the equity market in order to capitalize the high interest rates. The reverse scenario can be anticipated in case of sudden drop in interest rates. This change in economic behavior by investors is not motivated by the behaviors of others rather it is driven by what we call fundamnetal factors. Kremer & Nautz (2013) recognize "unintentional herding is basically fundamental driven and emerges becuase market participants with similar correlated private information make similar conclusions regarding a particular stock investment".

The motivation of spurious herding stems from the fact that the reactions of the investors are coming in response to any public information realesed in the market rather than intending to duplicate the behaviors of other market players. For example, if a pharmaceutical company releases a news about the introduction of a newly developed cancer treatment, investors active in the equity market may revise their analysis of the firm's expected future payoff and have the preferences to buy its shares. This behavior is considered to be in conformity with the efficient market hypothesis (EMH) in the sense that investors actions will bring back the share price of the company to its newly fundamentally justified level. That's why we can argue that spurious herding can always produce the efficient outcome in the market.

6.5 Literature Review

Herding behavior has always been a subject matter for researchers, academicians, and policy makers for grasping the dynamics of financial markets. Herding is the behavioral tendency of the equity market participants to abandon their own judgment to emulate collective actions in the market, which may lead to correlated trading patterns (Nofsinger & Sias, 1999; Welch, 2000; Hwang & Salmon, 2004). In the case of trait events in the market, herding behavior could arise due to mistaken beliefs that others may have better information (Avery & Zemsky, 1998). This chapter attempts to develop the existing body of literature surrounding herding behavior to shed light on motivations, methodological approaches, and consequences of its empirical findings among equity market investors and other participants. The development of literature review always provides as a roadmap to enable interested users to explore the background, motivations, and insights that have emerged from the scholarly research into herding behavior.

The empirical studies on behavioral finance came into attention mainly in the early 1990s to investigate why aggregate equity market devatiated from its fundamental value or why the actual investment decisions bevavior of the market partcipants are not congruous with the underlying finance theories. A voluminous of researches were conducted in behavioral finance literature on herding behavioral bias in the international equity markets irrespective of the nature and depth of the markets. The empirical findigs on the presence of herding behavior in the equity markets are inconclusive and contrasting.

6.5.1 Empirical Evidence on Herding Behavior

The study of Christie & Hunag (1995) is treated as trailblazer work in the empirical literature on herding behavior from the equity markets. They used a large data set of daily returns from the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from 1962 to 1988 and monthly returns data for New York Stock Exchange from 1925 to 1988 to investigate the presence of herding behavior. Christie and Hwang in their study first introduced the prominent market-wide based herding methodology of crosss-sectional standard deviations (CSSD), which is now being extensively adopted in herding behavior empirical literature. Results from the study evidenced that the analysis using both the daily and monthly returns dispersions were found inharmonious with the presence of herding behavior during periods of extreme market movements.

Another pioneer study in the literature of herding behavior was developed by Chang et al., (2000). They modified the Christie and Huang's (1995) cross-sectional standard deviations CSSD) methodology into the cross-sectional absolute deviations (CSAD) form to measure the herding behavior. The study considered five international equity markets (US, Hong Kong, Japan, Taiwan, and South Korea). They used data for all NYSE and AMEX firms from January 1963-December 1997 period, the daily returns data for Hong Kong equity markets (from January 1981-December 1995), for Japan (from January 1996-December 1995), for Taiwan (from January 1976-December 1995), and for South Korea (from January 1978-December 1995). The results revealed that US and Hong Kong equity market did not report the evidence of herding behavior but partial evidence was found in Japan, On the other hand, the two emerging equity markets of Taiwan and South Korea demonstrated strong form of herding behavior. One common feature observed in all the five equiy markets is that the level of increase in equity returns dispersions is higher during the positive market days in relation to the negaive markets.

The study from Tan et al. (2008) analyzed A-share and B-share stocks in Shanghai and Shenzen equity markets of China over the period 1994-2003. Findigs documented the existence of herding behavior under the scenario of upward and downward market condiions. But there was no evidence of asymmetry in case of B-share stocks in both Chinese equity markes which were dominated by foreign institutional investors. Caporale et al. (2008) tested the Athens Stock Exchange with the same methodology of Christie & Huang(1995), and Change et al. (2000) with specific focus on the stock price bubble in 1999. Results find that herd behavior is significantly stronger when observed at daily time intervals, thus revealing the transitory nature of this phenomenon. Upon evaluating the testing period in semi-annual sub-periods, it is discovered that herding occurred during the stock market crisis of 1999. Applying the Christie & Huang(1995), and Change et al. (2000) herding model, Kallinterakis & Lodetti (2009) found no evidence of herding in Montenegro equity market even after controlling the thin trading behavior of investors over the period of 2003 to 2008.

The four mediterranean equity markets are examined by Economou et al. (2011) with a data set over the period 1998 to 2008. They followed the Christie & Huang (1995), and Change et al. (2000) methodologies. Their study did not produce any evidence of herding behavior in Spain, Italy, and Greece but herding was present in Portugese equity market. Chiang et al. (2010) studied both Shanghai and Shenzen equity markets in China over the period of 1996 to 2007. The study applyed the least squares quantile regression model and found no evidence of herding behavior by investors documented for both B-share markets. Whereas they find evidence of herding in favor of both A-share markets even in the case of up and down markets. The herding behavior of investors was scrutinized by Demirer et al. (2010) in Taiwan equity market covering the period from January 1995 to December 2006. The study employed Christie & Huang (1995), Chang et al. (2000) and Hwang & Salmon(2004) methodology. The herding behavior was not observed in case of linear model but non-linear model produced the outcome in favor of herding behavior for all 18 sectors considered in the study. Herding behavior of investors tested for 18 countries including developed equity markets (France,Australia, Germany, Hong kong, the United Kingdom, and the United States, Latin Americal equity markets (Brazil, Argentina, Chilie, mexico), and Asian equity markets (Indonesia, Malaysia, Singapore, China, South Korea, Thailand, and Taiwan) in the study of Chiang & Zheng (2010). They applied daily industrial equity returns data over the period 1998 through 2009 and reported the evidence of herding in each country except the US and Latin American markets. Herding behavior was strongly observed in Asian equity markets specifically in rising market phase. But evidence of herding formation found in the US and Latin American markets during the crisis period.

The herding behavior at aggregate market level and at the industry level are performed by Khoshsirat & Salari (2011) in Tehran Stcok Exchange for the period April 10, 2001 to July 11, 2009. The results manifested that herding effect was only present for automobile and minerals industries. Kapusuzoglu (2011) assessed the herding behavior of investors in Istanbul Stock Exchange using the cross-sectional dispersions of market index returns. Results supported the subsistence of herding behavior in both up movement and down movement market phases. The herding behavior was present in both Chinese and Indian equity market examined by the study of Lao & Singh (2011) over the period 1999 to 2009. They followed Cross-sectional absolue deviations (CSAD) method of Tan e al., 2008 and found that tendency of herding behavior of investors depends on equity marke conditions. In Chinese market, it was observed that herding effects are higher in decling market whereas, in India it was prevailed during rising market. But the degree of herding was lower in Indian equity market compared to the Chinese market.

Prosad et al. (2012) in another study signified the presence of herding behavior for the Indian equity market during the rising market state but it did not present in falling market phase. The market-wide herding behavior was also pronounced by the study of Lakshman et al. (2013) for Indian equiy market. They showed that presence of herding was on increased trends during the period 2003-2005 but started to decline beyond 2006.

Evidence of herding behavior was present in the Indian equity market from the study of Bhaduri & Mahapatra (2013) conducted over the period January 01, 2003 to March 31, 2008. This study used a different approach a of applying symmetric characteristics of the cross-secionak returns dispersion contrary to the traditional methodology to measure the herding behavior. Results indicated tha herding behavior was more pronounced during the 2007 crisis period. In addition, the study pointed out that the security returns dispersion was relaively lower in the Indian market during rising market than the decling market. Mobarek et al. (2014) investigated eleven European countries for the period 2001 to 2012 and report that herding behavior was prevailed for most of the countries during the global financial crisis under the scenarios of asymmetric market conditions. They also find that cross-sectional dispersion of returns in individual country is influenced by the cross-sectional dispersions of returns of other equity markets where Germany had the largest herding effects among these countries. A study from Poshakwale & Mandal (2014) confirmed the hering behavior of investors in Indian equity market. They applied a different methodology named Kalman filter to study the herding effects for the time period 1997 to 2012. The study also proved that herding behavior was more prevalent during the bear market than the bullish one. Other studies from the Indian equity market done by Garg & Jindal (2014) did not provide any evidence of herding behavior. Both the studies implemented Christie & Huang (1995) and Chang et al. (2000) methodologies to measure the herding effects of investors during the rising and falling market movements, before sub-prime crisis, during sub-prime crisis, and after sub-prime crisis conditions. In all cases, herding was not present in the Indian equity market.

Choi & Skiba (2015) tested institutional herding behavior in 41 countries using the quarterly data span from last quarter of 1999 to the first quarter of 2010. They focused on the relationship of herding behavior and level of information asymmetry in different dimensions. The results suggest that institutional investors have the greater tendency to herd in the market featured by low level of information asymmetry. The characteristics of culture and behavioral biases (overconfidence, excessive optimisam) were highlighted to examine the herding behavior in the study of Chang & Lin (2015). They measured the presence of herding behavior of investors in fifty equity markets over 46 years (from 1965 to 2011) and evidenced that investors' herding propensity was linked to the national culture and behavioral pitfalls. It was also found that behavioral factors had dominant influence on herding effects rather than cultural components. A study by Rahman et al. (2015) concentrated on herding behavior by retail investors in the Saudi stock market over the period January 2002 to March 2012. The results presented evidence of pervasive herding among the retial investors irrespective of up and down market conditions. But the level of herding intended to become stronger in case of positive market movement along with significant trading activity. The analysis also suggested that correlated trading behavior of investors are not likely to be related to the movement of fundamentals. The sudy of Economou et al. (2015) explored herding behavior in the contect of Euronext, a first ever merged members' exchange grioup comprises of four European equity markets: Belgium, France, the Netherlands, and Purtugal. Findings stated tha herding was detected for all equity markets after post-merger analysis but it was also significant for Portugal in before merger case. The study covers data from December 31, 1989 to October 31, 2009.

Angela-Maria et al. (2015) investigated herding behavior among investots in ten Central and Eastern European stock markets using the daily stock prices from 2003 to 2013. Employing cross-sectional absolute deviations (CSAD) approach of Chang et al.(2000), study found the presence of herding for various size-ranked portfolios in four GCC markets. Galariotis et al. (2015) evaluated herding towards aggregate market for the equity markets of US and UK in response to the macroeconomic announcement periods. Findings proved that the US investors display herding behavior during the periods when macroeconomic announcements are realesed into the market and there was herding spill-over-effcets from US to the UK equity market. The study also revealed that investors in the US herd because of fundamental and non-fundamental factors in crises periods but investors in the UK tend to herd owing to fundamental factors and only in bubbles periods. Galariotis et al. (2016) provided an examination of the relationship between investors herd behavior towards market consensus and equity market liquidity in G5 stock markets. The results strongly evidence the presence of herding behavior in case of high liquidity stocks for all markets except Germany. The robust outcome was also observed even under the context of different definitions of crisis period and different measurements of market liquidity.

An empirical investigation of herding in the U.S. stock market was investigated by Clements et al. (2017) for the period from 28 January 2003 to 16 September 2016. They applied a new approach of vector autoregressive (VAR) to measure the relationship between cross sectional return dispersion and market returns and found the presence of herding in all crises periods: the subprime mortgage, the European debt and the U.S. debt-ceiling and the Chinese stock market crash of 2015. These findings are inconsistent with the results obtained from the traditional methods where little evidence of herding is found in the US stock market.

Vo & Phan (2017) also found the presence of herding behavior in Vietnam stock market for the whole study period. The results are found to be more robust when samples are divided into different sub-periods: pre-crisis, during crisis, and post-crisis. Study also reports on the asymmetric herding of various market conditions. Blasco et al. (2017) focused on cultural, organizational and environmental factors to assess whether herding behavior was affected by those variables. They studied 35 international equity markets for the period from 2000 to 2015 and results indicate that some of these variables like technology, education play significant influence on herding effects and other factors like business style, development of financian markets may act as corrective influence on herding behavior. Guney et al. (2017) tested eight frontier African equity markets (Botswana, Kenya, Gana, Namibia, Nigeria, Tanzania, Zambia, and BRVM) during the period January 23, 2002 to July 15, 2015. Investors tendency to herd was present in all the equiy markets and the magnitude of herding incrased for smaller stocks. Asymmetric herding was significant during market volatility conditions but not found on conditions of market performances. Herding behavior of foreign investots was examined by Durukan et al. (2017) for Borsa Istanbul during financial crisis. The study employed state space and LSV model and provide support in presence of herding for the overall market but no found for foreign investors during and after the crisis periods. A study carrie out by Zheng et al. (2017) to examine the herding behavior within industries for nine Asian equity markets (China, Japan, South Korea, Thailand, Hong Kong, Singapore, Malaysia, Indonesia, Taiwan). The study documented that herding behavior of investors remained effective in all equity markets. The results also stated that industry level herding was more prevalent in falling markets with low trading volume activity for all the equity markets. Although industry level herding exists for all markets, but the level of herding varied from industry to industry within each equity market.

In another study, Chaffai & Medhioub (2018) examined the inestors’ herding behavior in the Islamic Gulf Cooperation Council (GCC) stock markets during the period January 03, 2010 to July 28, 2016. In this study, they employed the Generalized auto regressive conditional heteroskedasticity (GARCH)-type models and quantile regression analysis. Results proved that the presence of herding behavior was observed only during upward market conditions for GCC markets. Medhioub & Chaffai, (2019) attempted to focus on the herding behavioral bias of investors in sectoral analysis for Gulf Islamic stock markets. The study followed the methodology of Chiang & Zheng (2010) for the period September 2013 to October 2018. They reported the presence of herding behavior among investors in all sectors for Gulf Islamic markets specially in down market days. They also revealed that herding behavior also exists for some conventional sectors in up and down market cases. By employing cross sectional absolute deviation model, Akbar et al. (2019) examined herding behavior at both industry and market level in Pakistan. and found the robust presence in eight industry at industry level and in only one industry at market level. Stock trading volume also influences herding behavior for 5 out of 11 industry.

Herding behavior towards the market consensus in the Moscow Stock Exchnage examined by Indārs et al. (2019) with the focus on how herding intensity by investors are driven by fundametal factors or by non-fundamental factors. The study covers the dataset from April 01, 2008 to December 30, 2012 invloving daily closing prices for 120 listed companies in Moscow Exchange. In aggregare, herding behavior was not present in the Moscow equity market. Nevertheless, investors exhibit herding behavior during the period of extreme market movements, during the period of macroeconomic news releases, and during the period of oil price changes (specially during positive oil price changes). There was no convincing evidence of herding by investors, on overall, which are deemed to be motivated by fundamental factors. But during down market, the presence of non-fundamental herding found to be significant. Yao & Tangjitprom (2019) did their study to capture the herding behavior of market participants in six ASEAN equity markets during the period 2009 to 2016. They emplyed the methodology of Chang et el. (2000) to examine the response of herding behavior with respect o the asymmetric equity market conditions like market trading volume, market volatiltiy. There was no imitating behaviors of investors observed in all the equity markets except Vietnam market. The study also reported that US equity market did not have any influential role to affect the herding behavior in each ASEAN equity market. Vo & Phan (2019) also found the evidence of herding in Vietnam stock market for the whole study period as well as for all sub-periods. They applied both Christie & Huang (1995) and Chang et al. (2000) methodologies to detect herding behavior for the daily data over the period 2005-2017. The study also reports on the presence of asymmetric herding under different market conditions. In another study, Vo and Phan (2019) investigates the impact of idiosyncratic volatility and herding behavior among investors in Vietnam stock market. Results indicate that herding behavior prevails in the market, and it displays distinct patterns for different stock portfolios depending on the level of idiosyncratic risk. Using daily stock data from January 4, 2010 to December 29, 2017, herding behavior market was examined by Hefnaoui (2019) in Moroccan stock market. By employing cross-sectional absolute deviation (CSAD) they did find the presence of herding in both upward and downward markets. The outcome supported that frontier market possesses low level of transparency and quality of information which may lead investors to herd.

Ju (2020) applied the cross-sectional absolute deviation model on China's A- and B-share markets and detect that herding is present on both types of markets. It reports that A-share market investors growth stock portfolios under both up and down markets but they only herd for value stocks in down market, therefore leading the whole herding behavior to be pronounced in down market. Herding on B-shares market is robust for all investment styles. Recent study conducted by Chen (2021) to measure the herding behavior of individual investors in Chinese A-share markets. They used daily adjusted closing price for both Shanghai and Shenzen A-share markets for the period from July 2016 o July 2019. By applying the Chang et al. (2000)

methodology of cross-sectional absolute deviations (CSAD), they found the influence of herding behavior for both A-shares markets in China. In comparison between these two markets, the level of cross-sectional absolute dispersion was higher in Shenzen market than the Shanghai equity market. Asymmetric herding behavior during the up and down markets of Istanbul Stcok Exchange was examined by Adem (2020). The study used the daily, weekly, and monthly sectoral data starting from 2000 to 2018. They investigated the herding behavior with Christie & Huang (1995) methodology of cross-sectional standard deviations(CSSD) and Chang et al. (2000) model of cross-sectional absolute deviations (CSAD). The empirical findings displayed that the herding behavior of investors in Istanbul equity market is more stronger in the declined market rather than the increased market. Furthernore, it was more prominent in case of daily returns compared to the weekly and monthly returns.

Herding was examined in the Mongolian stock market for dataset spanning from 1999 to 2019, incorporating both bullish and bearish market periods, as well as periods of high and low market volatility (Batmunkh et al., 2020). Study also considered the impact of four significant events that happened during the period: the establishment of the Finance Regulatory Committee of Mongolia (FRCM), the Global Financial Crises, Mongolia's inclusion in the FTSE Russell Watch list, and the economic boom of 2011. By using a cross-sectional absolute deviation (CSAD) model, clear evidence of herding behavior was observed across all of these events.

Herding behavior was examined for four frontier markets Bulgaria, Croatia, Romania and Slovenia using the Chang et al. (2000) cross sectional dispersion model for the period over 2000-2016. (Economou, 2020). The results indicate that Romania has the intensive evidence of herding compared to other countries across different estimations; Herding was also observed during global financial crisis and Euro Zone accession crisis events for each country.

Espinosa-Mendez & Arias (2021) examines whether the COVID-19 pandemic impact herding behavior in five European stock markets like France, Germany, Italy, United Kingdom, and Spain. By using a sample over the period from January 03, 2000 to June 19, 2020, study obtained substantial empirical evidence indicating that the COVID-19 pandemic has intensified the occurrence of herding in the European stock markets. The model proposed by Chang et al. (2000) was used in the study to measure the herd behavior. Arjoon et al. (2020) tested herding behavior in the Singapore stock market and discovered the clear existence of herding at both portfolio and aggregate market level. Herding is spurious and intentional for larger portfolios and the overall market, but only intentional for smaller portfolios. Significant evidence of cross-portfolio herding is also seen. The study also finds that herding is more common in rising market situations and demonstrated that market volatility and liquidity dynamics make herding worse for overall market and each portfolio size. The cross-sectional absolute deviation (CSAD) model of Chang et al. (2000) was used for the sample period 2005-2018.

Choi & Yoon (2020) employed the Cross-Sectional Absolute Deviation (CSAD) approach, along with the quantile regression method in order to test herding behavior in Korean stock market.

Herding behavior is evident during periods of market decline and adverse herding behavior is prevalent during periods of low trading volume and low volatility. Results from the quantile regression discover the presence of herding behavior in both the lower and upper quantiles of market returns. This study also identifies the occurrence of adverse herding behavior indicating that investors tend to herd together during extreme market conditions.

Dhall & Singh, (2020) employed the widely implemented model proposed by Chang et al. (2000) to investigate the presence of herd behavior in Indian stock market. By utilizing the daily stock prices data of 191 firms spanning from 1 January 2015 to 1 June 2020, the results found for both the entire sample period and the pre-COVID-19 outbreak period (1 January 2015 to 29 January 2020) confirm the absence of herding formation at the industry level. Clear evidence of herding behavior is found under the conditions of both bull and bear markets during the post-COVID-19 outbreak period (1 January 2020 to 1 June 2020). They conclude that the COVID-19 pandemic has provoked the emergence of herding behavior at the industry level, which might help investors in formulating their trading strategies in the context of the COVID-19 regime.

Herding behavior was more intensive after the COVID-19 period compared to the before Pandemic in all six Eastern European stock markets (Russia, Poland, The Czech Republic, Hungary, and Slovenia). Fang et al. (2021) applied cross sectional absolute deviation CSAD) model to detect herding for the period 2010-2021. Findings reveal that the COVID-19 pandemic tends to increase the influence of international market returns on herding behavior within the specific stock markets under consideration. The COVID-19 strengthens the transmission effect of regional herding in these European markets. The findings help policy makers to actively supervise investors trading behavior to reduce herding behavior, and to counteract the reinforcement of both global market returns and regional return dispersion on herding during the period of the pandemic. Using the Cross-sectional Standard Deviation (CSSD) and the Cross-sectional Absolute Deviation (CSAD) models, Jiang et al. (2022) investigated herding behavior during the Covid-19 period for six Asian stock markets (Japan, South Korea, China, Hong Kong, Singapore, and Taiwan) over the period from February 1, 2020 to January 31, 2021. Both these models were aligned with the Markov-switching regression and HS model in order to effectively identify both the presence and magnitude of herding. Empirical findings demonstrate the clear presence of herding during the Covid-19 and successfully captured a significant increase in the magnitude of herding during the market crash that occurred in March 2020.

Pochea (2021) examined investors' tendency to follow the market consensus in both the US and European stock markets during the period from January 5, 2006 to September 30, 2020. It is pointed out that the uncertainty stemming from the outbreak of the COVID-19 pandemic has intensified the observed herding behavior. In addition, non-fundamental information has been found to be the driving force behind this behavior, which is more present in both markets during unconventional events. The results also provide significant evidence of herding during periods characterized by investors' sentiments and emotions. Ah Mand et al. (2023) used daily data for the period of 1995–2016 to test herding behavior applying Chang *et al.* (2000) model for

Malaysian stock market. The findings state that investors in Shariah-compliant stocks exhibit herding behavior during the upward and downward market. No herding was present for conventional stocks. Study also finds presence of herding for the whole market during only up market. Moreover, the robustness of these results is consistent with regards to the impact of both the Asian and global financial crises.

A new study examined by Espinosa-Méndez & Arias (2021) considering the impact of COVID-19 on the financial markets of Oceania. The study focuses on determining whether the COVID-19 pandemic exerts an influence on the imitating behavior of investors in the Australian stock market. By incorporating an intensive sample encompassing all corporations listed during time spanning from June 10, 2008 to June 19, 2020, findings indicate that the COVID-19 pandemic significantly amplifies the occurrence of herding behavior. The results also illustrate that herding behavior was manifested during periods characterized by crises and extreme circumstances.

The herding measurement in the markets of Spain and Portugal was done by Ferreruela & Mallor (2021) by utilization the cross-sectional dispersion of returns. The dataset of the study encompasses the time covering from January 2000 to May 2021 and adopted both cross sectional return dispersion models proposed by Christie & Huang (1995) and Chang et al. (2000). The outcomes reveal that herding is observed to a greater extent in periods preceding the crisis. However, during the financial crisis herding behavior disappears in the market and it reappears with less intensity after the Covid-19 crisis. Conversely, herding behavior is generally not detected during the COVID-19 Pandemic. Herding is observed during the Pandemic on days of high-level volatility.

Jirasakuldech & Emekter (2021) discovered herding behavior among investors in Thailand stock market under varying market conditions and crisis periods. The findings display that herding tendencies occur during extreme market movements characterized by either negative or positive returns within the context of a declining market, on days with substantial trading volume, during 1997 Asian crisis, and during economic downturns. The introduction of internet trading platforms, bond electronic trading exchanges, and future electronic exchanges in Thailand did not lead to any presence of herding behavior among investors.

Bouri et al. (2021) empirically tested herding behavior for 49 individual stock markets during Covid-19 Pandemic. They applied Chang et al. (2000) return dispersion-based methodology to detect herding behavior over the period of 1 January 2019 to 10 August 2020. The findings report a strong relationship between herd formation in stock markets and COVID-19 induced market uncertainty and is more pronounced for emerging stock markets and for some European PIIGS stock markets that include some of the hardest hit economies in Europe by the pandemic

Bogdan et al. (2022) studied whether herding behavior was present during COVID-19 period in European stock markets. The well-known models proposed by Christie & Huang (1995) and Chang et al. (2000) are used in the study for measuring herd behavior. The findings indicate that herding is most prominent in emerging markets, subsequently trailed by frontier markets and developed markets. Therefore, the findings have relevant implications for both individual and institutional investors in their perusal of attaining effective risk diversification, as well as for financial authorities in their endeavor to establish regulations to reduce the escalation of herd behavior. The study considers the daily index data for 15 European countries spanning from 1 January 2018 to 28 January 2022.

Maquieira & Espinosa Méndez (2022) examine herding behavior in the Chinese stock markets during the COVID-19 pandemic by adopting the cross-sectional absolute deviation (CSAD) model proposed by Chang et al. (2000) to identify presence of herding behavior between January 30, 2001, and June 12, 2020. Findings imply the existence of herding behavior during the observed period and become more pronounced after the COVID-19 crisis. They also revealed the occurrence of asymmetric herding conditioned on market returns and volatility. The outcomes demonstrate that when the market return is high and the volatility is low, the trend of herding behavior becomes more prevalent. The results also remain consistent across different time periods, evidencing the robustness of study findings.

Bangalore Nagendra (2022) investigates Irish stock market to measure the herding behavior not only in standard condition but also during significant upswings and severe downturns. In order to analyze the phenomenon of herd behavior, study uses daily returns from 2015 to 2021and employed two prominent models by Christie & Huang (1995) and Chang et al. (2000). The results indicate an absence of evidence supporting herding during periods of extreme market conditions as well as for normal conditions. The coefficients of herding not found significant under the both normal and asymmetric market conditions in the BRICS equity market except for China and South Africa during the study period January 2011 until May 2019. (Shrotryia & Kalra, 2022). They employed the cross-secional absolute model (CASD) by Chang, Cheng, & Khorana (2000) and quantile regression to measure the herding components using the multiple data structure(daily, weekly, and monthly). Results also reveal that contagion effects prevail between the US and the BRICS equity markets except China implying that the US market can significantly influence the herding behaviors in other equity markets.

Ampofo et al. (2023) examined the two developed stock markets, the USA and UK. Using the daily stock index data from December 5, 2017 to February 28, 2022, they applied quantile regression in addition to return dispersion model of Chang et al. (2000). The results indicated that herding behavior was not present before Covid-19 period in both the USA and UK bullish markets but discovered in both countries bullish markets during the Covid-19 period. No herding was documented in the bearish markets of both countries.

The Vietnam stock market was investigated by Dam et al. (2023) during COVID-19 period and reported evidence of herding in the period of global Covid-19 crisis but not in the PreCovid-19 period. It also implies that herding intensity became stronger as the Pandemic gradually deteriorates. They applied Chang et al. (2000) model of the cross-sectional absolute deviation (CSAD) for both daily and weekly trading data from January 2018 to December 2021. The findings may help regulator to reduce any stock market crash for its overall development.

Hasan et al. (2023) examined the herding behavior for 33 global stock markets considering the four international crises: The Euro Zone crisis, China's market crash (2015-2016), aftermath of the Brexit vote, and the COVID-19 Pandemic. The study finds strong evidence of herding driven by non-fundamental information in negative market conditions for all countries. They also find that herding behavior increases with the associated increase in systematic risk. To detect herding behavior, they applied quantile regression models.

Nguyen et al. (2024) applied both cross sectional absolute deviation (CSAD) and quantile regression models to measure herding behavior in the Vietnamese stock market from January 2016 to May 2022 and found that herd behavior was more pronounced in bearish market condition than the bullish period. Vidya et al. (2023) examined herding behavior in eight Asian stock markets using the methodology suggested by Chang et al. (2000) and Chiang & Zheng (2010) and results support the robust presence of herding in Vietnam, Indonesia, India, South Korea and Singapore during up market condition. Herding was also present in bearish market for both Indonesia and Vietnam. Study also finds herding for India, Indonesia, and Vietnam during COVID-19 period while it was stronger after COVID-19 crisis for China and Vietnam.

Hakmaoui & Jebari, (2023) tested herding behavior in the stock markets of USA, France, Morocco, and Tunisia. Results represent the existence of herding in the USA and Morocco but not in the French and the Tunisian stock markets. It also indicates that herding is more pronounced in the frontier markets than the developed markets. Both the cross-sectional absolute deviation (CSAD) and quantile regression models were used in the study.

6.5.2 Evidence from Bangladesh Equity Market

There are only two studies conducted on herding behavior in the Bnagladeshi equity market. Ahsan & Sarkar (2013) examined herding behavior for the Dhaka Stock Exchnage over the period January 2005 to December 2011. He employed the methodology of Christie and Huang (1995) and Chang et al. (2000) to measure the herding behavior and findings reveal investors in Bangladesh equity market do not imitate the others decisions.

Khan & Imam (2023) investigate herding behavior in the Bangladesh equity market covering the data set from January 03, 2007 to December 29, 2011. Cross-sectional absolute deviation (CSAD) has been employed in the study and findings suggest that herding behavior does exist in the Bangladesh equity market. The study also finds the presence of potential asymmetries in herd behavior conditioned on trading volume. The results suggest that herding behavior is more pronounced when market trading volume is high and during extremely upward market state.

In behavioral finance literature, research on herding behavior can be categorized into two broad dimensions: herding towards certain stocks using micro data, that is, data on stock level characteristics. This is done by professional institutional investors. The second dimension is market wide herding focuses on measuring herding tendency of investors using aggregate market data. The summary of literature review on these two research dimensions is presented Table 6.1 through Table 6.5.

Table 6.1: Summary of empirical studies on Institutional herding using LSV(1991) Model

Empirical Study	Time Period	Country	Presence of Herding
Grinblatt,Titman & Wermers (1995)	1974-1984	US	Yes
Wermers (1999)	1975-1994	US	Yes
Choe et al. (1999)	1996-199	Korea	Yes
Lobao & Serra (2007)	1998-2002	Portugal	Yes
Bowe & Domuta (2004)	1997-1999	Indonesia	Yes
Sias (2004)	1975-1994	US	Yes
Kim & Nofsinger (2005)	1975-2001	Japan	Yes
Wylie (2005)	1986-1993	UK	Yes
Walter & Weber (2006)	1998-2002	Germany	Yes
Alemanni & Ornelas (2006)	2000-2005	Emerging Markets	Mixed
Voronkova & Bohl (2005))	1999-2001	Poland	Yes
Puckett & Yan (2007)	1999-2004	US	Yes
Lakshman, Basu, & Vaidyanathan (2013)	1996-2008	India	Yes
Choudhary, Singh, & Soni (2021)	1999-2017	India	Yes
Sahoo, Rajvanshi, & Syamala (2023)	2003-201	India	Yes

Note: LSV (1991) is an approach used Lakonishok, Schleifer and Vishny (1991) to measure herding behavior for institutional investors.

Lakonishok, Schleifer and Vishny (LSV, 1991) have been treated as the pioneers of institutional herding model. According to LSV (1991), herding is the tendency of a group of professional managers to buy and sell particular stocks simultaneously compared to what would be expected if they traded independently. They deal with a subset of market participants over time making decisions regarding the market. Table 6.2 presents a brief summary of empirical works on institutional herding using the LSV(1991) model, which is not the subject matter of our research.

In this part, we present a summary of empirical findings from existing literature on herding behavior across different equity markets classified by MSCI (Morgan Stanley Capital Investment) . MSCI evaluates equity markets around the world every year to classify as a developed, emerging, and frontier markets on the basis of economic development, size and liquidity requirements, and market accessibility.

Table 6.2: Summary of empirical studies on herding evidence from developed equity market				
Empirical Study	Time Period	Methodology	Country	Presence of Herding
Hachicha (2010)	2000-2006	CSSD	Canada	Yes
Boutabba (2014)	2002-2006	CSSD,CSAD	US, France	No
Economou et al. (2015)	1989-2009	CSSD	France, Belgium, Portugal, Netherlands	
Galariotis et al. (2015)	1989-2011		US, UK	Yes
Braga (2016)	2000-2016	CSSD,CSAD	Spain, Portugal	Yes
Galariotis et al. (2016)	2000-2015	CSAD	G-5 Stock Market	Mixed
Clements et al. (2017)	2003-2016	VAR	US	Yes
Graisse (2021)	2006-2020	CSAD	US and Europe	No
Espinosa-Mendez et al. (2020)	2000-2020	CSAD	Germany, France, Italy, Spain, UK	Yes
Arjoon et al. (2020)	2005-2018	CSAD	Singapore	Yes
Espinosa-Méndez & Arias, (2021)	2008-2020	CSAD	Australia	Yes
Pochea (2021)	2006-2020	CSSD,CSAD	US, Europe	Yes
Ferreruela & Mallor, (2021)	2000-2021	CSSD,CSAD	Spain, Portugal	Mixed
Bangalore Nagendra,(2022)	2015-2021	CSSD,CSAD	Ireland	No
Ampofo et al., (2023)	2017-2022	CSAD, QR	US, UK	Mixed

Note: CSSD is the cross-sectional standard deviation, CSAD is cross-sectional absolute deviation, QR is the quantile regression, and VAR is vector autoregression

Table 6.3: Summary of empirical studies on herding evidence from Mixed equity market

Empirical Study	Time Period	Methodology	Country	Presence of Herding
Christie & Huang(1995)	Range from 1963 to 1997	CSSD	US, Hong Kong, Japan, Taiwan, Korea	Mixed
Hwang & Salmon (2004)	1993-2002	State Space	US, Korea	Yes
Chiang & Zheng, (2010)	1998-2009	CSAD	18 Countries	Mixed
Mobarek et al. (2014)	2001-2012	CSAD	15 European Stock Market	Mixed
Chang & Lin (2015)	1965-2011		50 Stock Market	Mixed
Angela-Maria et al. (2015)	2003-2013	CSAD	10 European Market	Mixed
Blasco et al.(2017)	2000-2015		35 Countries	Mixed
Medhioub & Chaffai, (2019)	2013-2018	CSAD	GCC Market	Mixed
Chang et al. (2000)	Range from 1963 to 1997	CSSD, CSAD	US, Hong Kong, Japan, Taiwan, Korea	Mixed
Chaffai & Medhioub, (2018)	2010-2016	GARCH, QR	GCC Stock Market	Mixed
Zheng et al. (2017)	1993-2013	CSAD	9 Asian Market	Mixed
Yao & Tangjitprom (2019)	2009-2016	CSAD	ASEAN Market	No
Hasan et al. (2023)	2000-2022	CSAD	33 Global Markets	Yes
Bogdan et al. (2022)	2018-2022	CSSD, CSAD	15 European Market	Mixed
Vidya et al. (2023)	2018-2022	CSAD	8 Asian Market	Mixed
Bouri et al. (2021)	2019-2020	CSAD	49 Stock Market	Mixed

Note: CSSD is the cross-sectional standard deviation, CSAD is cross-sectional absolute deviation, QR is the quantile regression, and GARCH is the generalized autoregressive conditional heteroskedasticity.

Table 6.4: Summary of empirical studies on herding evidence from emerging equity market				
Empirical Study	Time Period	Methodology	Country	Presence of Herding
Caporale et al. (2008)	1998-2007	CSSD, CSAD	Greece	Yes
Tan et al. (2008)	1994-2003	CSSD, CSAD	China	Yes
Kallinterakis & Lodetti (2009)	2003-2008	CSSD, CSAD	Montenegro	No
Chiang et al. (2010)	1996-2007	QR	China	Yes
Demirer et al. (2010)	1995-2006	CSSD, CSAD, State Space	Taiwan	Mixed
Khoshsirat & Salari, (2011)	2001-2009	CSSD	Iran	No
Lao & Singh, (2011)	1999-2009	CSAD	China, India	Yes
Kapusuzoglu (2011)	2000-2010	CSSD, CSAD	Turkey	Yes
Lakshman et al. (2013)	1996-2008	LSV, State Space	India	Yes
Prosad et al. (2012)	2006-2011	CSSD, CSAD	India	No
Poshakwale & Mandal (2014)	1997-2012	Kalman Filter	India	Yes
Garg & Jindal (2014)	2000-2012	CSSD, CSAD	India	No
Filip et al., (2015)	2008-2010	CSAD	Czech Republic, Poland, Hungary	Yes
Rahman et al. (2015)	2002-2012	CSAD	Saudi Arabia	Yes
Ababio & Mwamba (2016)	2010-2015	CSAD	South Africa	Yes
Durukan et al. (2017)	2006-2015	State Space, LSV	Turkey	Mixed
Indārs et al. (2019)	2008-2012	CSAD	Russia	No
Choi & Yoon (2020)	2003-2018	CSAD, QR	South Korea	Mixed
Dhall & Singh, (2020)	2015-2020	CSAD	India	Mixed
Allam et al. (2020)	Mar 2020-Jul 2020	CSAD	Egypt	Mixed
Adem, (2020)	2000-2018	CSSD, CSAD	Turkey	Yes
Chen (2021)	2016-2019	CSAD	China	Yes
Ju, (2020)	1992-2007(A) 1994-2007(B)	CSAD	China	Yes
Ah Mand et al. (2023)	1995-2016	CSAD	Malaysia	Yes
Bharti & Kumar (2022)	2010-2020	CSAD	India	Yes
Mishra & Mishra (2023)	2019-2020	CSAD,GARCH	India	Yes
Maquieira & Espinosa Méndez (2022)	2001-2020	CSAD	China	Yes
Fang et al. (2021)	2010-2021	CSAD	Czech, Republic, Poland, Hungary Croatia	Yes
Jirasakuldech & Emekter, (2021)	1988-2015	CSSD,CSAD	Thailand	Yes

Loang & Ahmad, (2022)	2016-2020	CSAD, QR	Malaysia	Yes

Note: CSSD is the cross-sectional standard deviation, CSAD is cross-sectional absolute deviation, QR is the quantile regression, GARCH is the generalized autoregressive conditional heteroskedasticity

Table 6.5: Summary of empirical studies on herding evidence from frontier equity market

Empirical Study	Time Period	Methodology	Country	Presence of Herding
Le & Truong (2014)	2006-2012	CSSD, CSAD	Vietnam	Yes
Shah et al. (2017)	2004-2013	CSAD	Pakistan	Mixed
Akbar et al. (2019)	2000-2014	CSAD	Pakistan	Mixed
Guney et al. (2017)	2002-2015	CSSD, CSAD	Eight African Country	Yes
Vo & Phan (2017)	2005-2015	CSSD, CSAD	Vietnam	Yes
Vo & Phan (2019)	2005-2017	CSSD, CSAD	Vietnam	Yes
Vo & Phan (2019)	2005-2016	CSSD, CSAD	Vietnam	Yes
Batmunkh et al., 2020)	1999-2019	CSAD	Mongolian	Yes
Economou F. (2020)	2000-2016	CSAD	Balkan Region	Yes
Hefnaoui, A. (2019)	2010-2017	CSAD	Morocco	Yes
Hassan & Jamil (2021)	2007-2020	CSSD, CSAD	Pakistan	Yes
Kashif et al. (2021)	2000-2016	CSSD,CSAD, State Space	Pakistan	Yes
Shrotryia & Kalra (2022)	2011-2019	CSAD, QR	BRICS Market	Mixed
Dam et al. (2023)	2018-2021	CSAD	Vietnam	Mixed
Nguyen et al. (2024)	2016-2022	CSAD, QR	Vietnam	Yes
Jabeen et al. (2023)	1998-2008	CSSD	Pakistan	No

Note: CSSD is the cross-sectional standard deviation, CSAD is cross-sectional absolute deviation, QR is the quantile regression

6.6 Research Question and Hypotheses Development

Examination of herding behavior has become very important for measuring market efficiency, price formation and investor rationality in financial markets. In the context of frontier markets, such as Bangladesh, where information asymmetry, institutional participation and behavioral biases can be important factors, the study of herding behavior is even more important. Investors in these markets can be prone to trading with collective feeling and market tendencies as opposed to the fundamentals of firms hence correlated trading patterns which can follow and increase market volatility and mispricing. To systematically handle these questions, this paper develops a series of research questions and hypotheses to test the existence, variation and asymmetry of the herding behavior in the Bangladesh equity market. The research question one will be aimed at determining whether the participants in the market are herding in their investment decision making. The second research question explores whether the herding inclination varies between different market conditions i.e. between bullish and bearish markets hence establishing market dynamics throughout time. The third research question is whether there is asymmetry in the herding behavior based on various market conditions, especially in a time of positive and negative market returns.

Out of these research questions, some testable hypotheses are formulated to furnish empirical evidence on whether herding behavior exists in the Bangladesh equity market and its nature. These hypotheses inform economic analysis and enable the conclusion of the behavioral tendencies of investors in different market settings

Research Question 1: Do market participants in Bangladesh equity market tend to exhibit any herding behavior in their investment decision behavior?

Voluminous empirical studies have documented the existence of herding behavior in the equity market in all parts of the world. Some of them are in advanced equity markets (such as Mobarek et al., 2014; Clements et al., 2017), emerging markets (such as Lao & Singh, 2011; Yao et al., 2014; Ganesh, Gopal, & Thiyagarajan, 2018), and frontier markets (such as Shah et al., 2017; Vo & Phan, 2016). Behavioral finance posits that herding behavior is one of the common biases observed in the equity market may arise due to cognitive and psychological behavior of investors, which can distort the equilibrium prices and enhance the market inefficiency. Understanding whether investors tend to follow the actions of others rather than their own fundamental analysis still remain a subject matter under empirical investigation for any frontier equity market. The first research question has led to the development of the following two hypotheses.

Hypothesis 1: Herding behavior may exist in normal equity market conditions.

The key assumption of developing the herding behavior specification by Christie & Huang (1995) is that investors are more likely to abandon their own beliefs in favor of overall market consensus during the period of extreme market movements. They argue that if investors tend to herd, security returns should not deviate too far from the overall market return, and this behavior will lead to an increase in equity return dispersion at a decreasing rate. Empirical studies supported the presence of herding during market turbulence period (Bhaduri & Mahapatra, 2013, Bernales et al., 2020; Vo & Phan, 2016; Indars et al., 2019 Arjoon & Bhatnagar, 2017; Bouri, Gupta, & Roubaud, 2019).

Hypothesis 2: Herding behavior is more likely to occur in extreme market conditions.

Research Question 2: The tendency of herding behavior among market participants in Bangladesh equity market may vary across different market periods

Equity market experiences fluctuating patterns over time. It is expected that herding behavior among investors may be different depending on how we classify the market into different classifications. The one of the unique contributions of the study to herding literature is that we classified the equity market into bearish and bullish periods according to the Dow Theory. This research has led to develop the hypotheses 3,4,5 and 6.

Hypothesis 3: Herding behavior may be present when equity market experiences the bearish period.

Hypothesis 4: Herding behavior may be prominent when equity market experiences the bullish period.

Many studies documented that investors in equity market tend to herd during market crisis period which can lead to market volatility and inefficiency (Angela-Maria et al., 2013; Clements et al., 2017; Jirasakuldech & Emekter, 2021; Bogdan et al., 2022). Investors suppress their thinking and follow the market consensus during financial crisis expect that uncertainty regarding stock prices may increase.

Herding during equity market crisis period supported by the following empirical studies (Ramadhan & Mahfud, 2016; Shah et al, 2017; Economou et al., 2016; Litmi, 2017; Li et al., 2018). Adopting a larger data set in the study allows us to experience the two financial crises. First one is the crisis that arises due to endogenous shocks to the market that happened in 2011 (termed as stock market crash). The second crisis is due to exogenous shock to the market created from the worldwide COVID-19 pandemic.

Hypothesis 5: Herding behavior of investors seems to appear during the crisis period created by endogenous shocks to the equity market.

Mutual imitation to replicate the trading behavior of others among the equity market investors may be observed in case of crisis caused by the most recent COVID-19 pandemic. Many studies evidenced the presence of herding behavior in equity market during the COVID-19 period (Bouri, Demirer, Gupta, & Net, 2021; Bharti & Kumar, 2022; Ampofo et al., 2023).

Hypothesis 6: Herding behavior of investors seems to appear during the crisis period created by exogenous shocks to the equity market.

Research Question 3: Do market participants in Bangladesh equity market tend to exhibit any asymmetric herding behavior depending on different market conditions

The hypothesis 7 through hypothesis 12 have been formulated based on the research question 3.

Hypothesis 7: Herding behavior is expected to occur during the periods of negative market returns.

The presence of herding in up market returns days can be supported by the following empirical works Chang et al., 2000; Demirer et al., 2010; Chiang & Zheng, 2010; Ohlson, 2010; Philippas et al., 2013; Chen, 2021; Mobarek et al., 2014; Economou, 2020; Sadewo & Cahyaningdyah, 2022; Jiang et al., 2022; Vidya et al., 2023).

The literature also provides strong evidence of herding behavior during the up-market condition (Tan et al., 2008; Economou et al., 2011 and 2016).

Hypothesis 8: Herding behavior is expected to occur during the periods of positive market returns.

The market trading volume may have the significant influence on the tendency of herding behavior among equity market participants (Blume, Easley & O'hara, 1994; Gleason et al., 2004; Tan et al., 2008; Lao & Singh, 2011; Ouarda et al., 2013).

Hypothesis 9: Herding behavior may appear during the periods when market trading volume is high.

Hypothesis 10: Herding behavior may appear during the periods when market trading volume is low.

The herding tendency of market participants may respond differently, conditioned by market uncertainty and volatility. Investors would find themselves more comfortable to follow the market consensus during periods of high volatility and oscillation (Gleason, Mathur, and Peterson, 2004; Tan et al., 2008; Chiang & Zheng, 2010; Economou, 2020; Ferreruela & Mallor, 2021; Bharti & Kumar, 2022).

Hypothesis 11: Herding behavior may be present during periods of high market volatility.

Hypothesis 12: Herding behavior may be present during the periods of low market volatility.

6.7 Data and Methodology

6.7.1 The Data

The data for this essay analysis comprises the daily closing price, trading volume, and market capitalization for each firm listed on the Dhaka Stock Exchange (DSE) in Bangladesh. All data used covers the period from January 03, 2010 to December 30, 2021. All data were collected from the Dhaka Stock Exchange library and compiled according to research objectives. We constructed two market variables: Aggregate daily market returns and daily market trading volume. Aggregate Market returns are calculated by averaging the daily adjusted return of all stocks traded on each day, known as equally weighted market returns. While daily market trading volume is calculated by summing up the individual trading volume of all stocks traded on each day. After considering non-synchronized trading and missing information constraints, we selected 290 companies for our research. The realized equity return for each individual company is determined as:

$$R_{i,t} = In\left[\frac{P_t}{P_{t-1}}\right] * 100 \tag{6.1}$$

Where, $R_{i,t}$ is the realized equity return of company I at time t. P_t *and* P_{t-1} are the adjusted closing price of each company at time t and t-1.

To investigate herding behavior, we classified whole sample into bearish, bullish, crisis, extended crisis, and Covid-19 markets to provide a valuable insight into how herding tendency of investors may vary under distinct market dynamics. The novel contribution of this research lies in how we classify bearish and bullish markets. Existing literature defines bearish market when the market return on a particular day increases and bullish one when the market return decreases on a particular day. In this study, we segregated bearish and bullish markets according to the principles of the Dow Theory. The Dow Theory, a widely studied applied technique in technical analysis, provides a framework to understand the equity market trends and helps market participants to identify the potential changes in the market directions. To the best of my knowledge, no single research on herding behavior has used Dow Theory to classify the equity market as bearish and bullish.

6.7.2 Methodology

The mainstream empirical research methodology on herding behavior can be organized into two categories (Spyrou, 2013). The methodology of the first category focuses on measuring herding on specific types of investors such as institutional investors. The second category investigates herding behaviors by entire equity market movements, a collective behaviors of all market participants rather than focusing on a particular market segment. This methodology aspect is prominently accepted as market-wide herding.

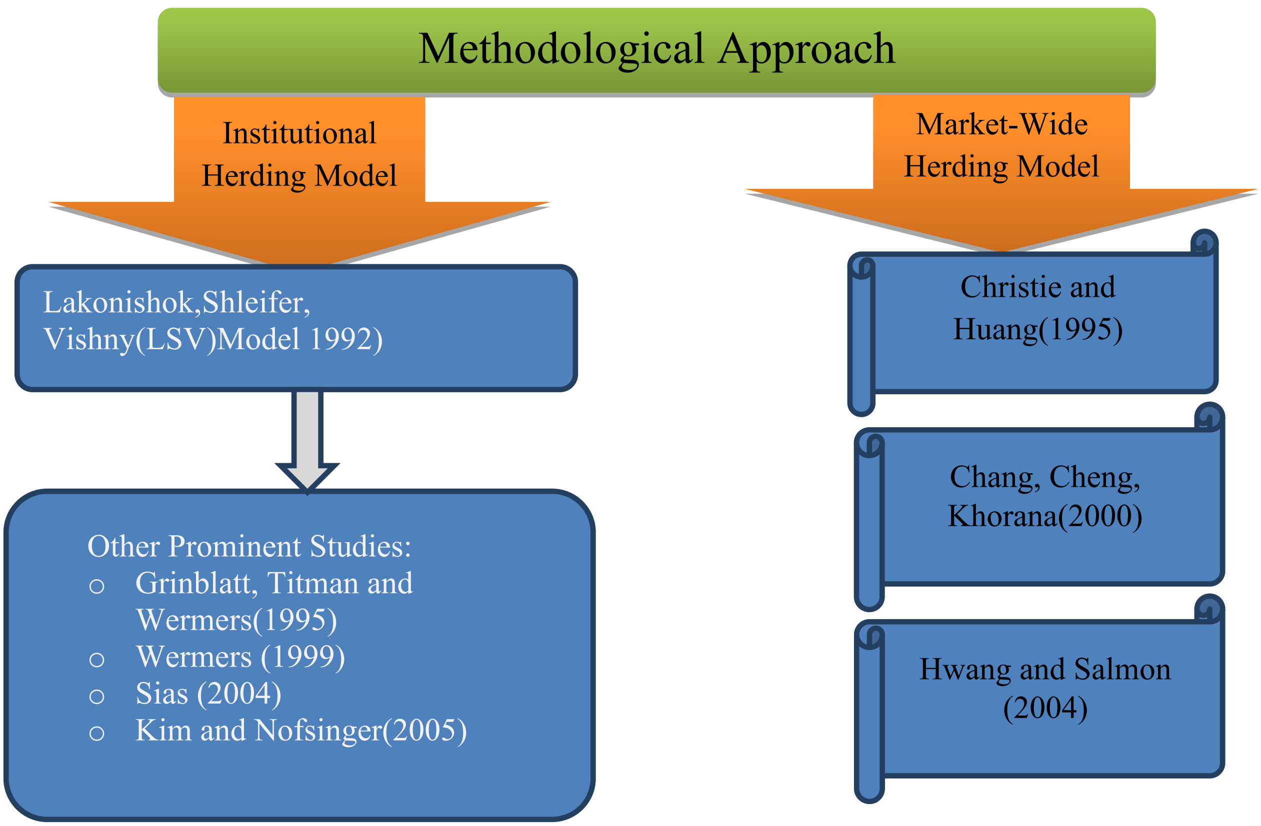


Figure 6.1: Development of the methodological approaches to herding behavior from existing literature

Figure 6.1 presents the methodological approaches developed from the existing herding literature, where first category was proposed by Lakonishok et al. (1992) and improved by Sias (2004) and others. The second measure is proposed by Christie & Huang (1995), Chang et al. (2000), and Hwang & Salmon (2004) and has been widely empoyed in the international literature (Spyrou, 2013).

This research attempts to investigate market wide herding behavior among investors in the Bangladeshi equity market. Market wide herding measures are based on the equity return dispersions and state space models. The first dispersion model of Christie & Huang (1995) measures herding behavior estimating the cross-sectional standard deviation (CSSD) of returns. The second dispersion model of Chang et al. (2000) measures herding tendency of investors estimating cross-sectional absolute deviation (CSAD) of returns. If herding exists, individual equity returns will not deviate substantially from the overall market return, and resulting in a lower than normal equity dispersion. On the other hand, state space model of Hwang & Salmon (2004) measures herding behavior focusing on the cross-sectional variability of factor sensitivities.

Institutional Herding

The key intution about institutional herding points out that herding behavior took place among a particular segment of investors. This framework of detecting herding mainly concentrates on professional or institutional investors. We can define the methodological motivation of this measure is that it focuses on a subset of equity market participants conducted their tarding over a given period. This subset should be a market participants of homogeneous group namely, mutual funds managers, pension funds managers, hedge funds managers.

The first stream of empirical measure on institutional herding widely recognized is proposed by Lakonishok, Shleifer, & Visney (1992) also known as LSV measure. The LSV measure is calculated as follows:

$$Herding\,(HD)_{i,t} = \left|\frac{S_{i,t}}{n_{i,t}} - pt\right| - E\left|\frac{S_{i,t}}{n_{i,t}} - pt\right| \tag{6.2}$$

Where, $S_{i,t}$ is the number of institutional investors purchasing the stock i at time t

$n_{i,t}$ is the total number of institutional investors buying and selling the stock i at time t

pt refers to the probability for an institutional investor identifies as buyer in period t.

The first term of the model captures the intensity of the stock i to be more comprehensively bought or sold by institutional investors compared to all stocks in the portfolio. The second term is the natural disperson of transactions made by the investors. This dispersion is the outcome of the bionomial distribution generated for probability of pt and the number of drawings $n_{i,t}$. The value of herding zero means there is no herding by institutional investors whereas, the positive value of herding indicates the presence of herding.

6.7.2.1 Market-wide Herding

Market-wide approach is the aggregate attitudes of the investors in the market to follow the market portfolio. It spotlights the propensity of the cross sectional correlations of the entire market distributions or the distribution of the concerned population. To detect the market-wide herding behaving, the returns of the individual securities tend to be clustered around the market returns. This signifies that there will be a preference for the individuals to ignore their own information and just follow the market consensus.

The empirical studies on herding behavior in the field of behavioral finance mainly introdued in the early 90's. In this research, we employed two emphatic and extensively examinated market-wide herding methodologies extracted from the literature. First one is the model proposed by Christie & Huang (1995) and the second approach is developed by Chang, Cheng, & Khorana (2000).

The Methodology of Christie and Huang (CH)

Christie & Huang (1995) introduced this model in their paper titled "Do individual return herd around the market" published in 1995 to measure the herding behavior in the context of equity market. One of the important aspects of this model is it does not work in normal equity market condition and presume that investors have the inclination to imititate the market during its extreme phase. The rational asset pricing models predict that dispersion in cross-sectional returns will increase with the absolute value of the market returns during normal market periods since individual stocks vary in their sensitivity to the overall market returns. However, individual investors suppress their own private beliefs and base their investment decisions solely on the collective actions in the market during periods of extreme market movements. Therefore, individual equity returns will not deviate too far from the overall market return, and this behavior may lead to an increase in return dispersion at a decreasing rate or there should be a less than proportional increase or decrease in return dispersion. Thus, it is perceived that herding behavior will be more pervasive during periods of aggregate market movements rather than its normal condition. We can find that rational asset pricing models and herding behavior offer a contradictory predictions regarding the behavior of equity retrun dispersions.

To measure the presence of herding behavior, the CH's (1995) model relies on the dispersion measure narmed as cross sectional standard deviation of returns (CSSD) and calculated as:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} \frac{(R_{i,t} - R_{m,t}}{N-1}} \tag{6.3}$$

$R_{i,t}$ is the returns of security i at time t. $R_{m,t}$ is the cross-sectional average returns for N securities included in the market portfolio at time t.

Once the cross sectional standard deviation of returns are calculated, it is then regressed on the dummy variables introduced in the model capturing the two extreme phases of market movements. The model looks like as:

$$CSSD_t = \alpha + \gamma_1 D_t^U + \gamma_2 D_t^D + \varepsilon_t \tag{6.4}$$

Where, D_t^U takes a value of 1 if the returns of the market on day t lies in the extreme upper tail of the return distributions; and zero otherwise, and

D_t^D takes a value of 0 if the returns of the market on day t lies in the extreme lower tail of the retuen distributions; and zero otherwise.

We estimate equation (6.4) using 1%, and 5% of the observations in the upper and lower tail of the return distribution as our definition of extreme market movements.

The negaive and statistically significant value of coefficients $\gamma_1$and γ_2 will signify the presence of herding behavior in the market. The function of including the dummy variables is to capture the differences in herding behavior in case of extreme positive and negative market movements.

We modify the Christie and Huang's model specified in equation 6.4 by using the magnitude of market return with dummy variables at its tail distributions in following way:

$$CSSD_t = \alpha + \gamma_1 D_t^U |R_{m,t}| + \gamma_2 D_t^D |R_{m,t}| + \gamma_3 D_t^U R_{m,t}^2 + \gamma_4 D_t^D R_{m,t}^2 + \varepsilon_t \quad (6.5)$$

Where, D_t^U takes a value of 1 if the returns of the market on day t lies in the extreme upper tail of the return distributions; and zero otherwise, and D_t^D takes a value of 0 if the returns of the market on day t lies in the extreme lower tail of the distributions; and zero otherwise. $|R_{m,t}|$ is the absolute value of equally weighted market return, $R_{m,t}^2$ is the market return square. In order to detect herding behavior, the coefficients γ_3 and γ_4 should be negatively significant.

The Methodology of Chang, Cheng, and Khorana (CCK)

The second premier study examined on market-wide herding behavior in the equity market is the Chang, Cheng, & Khorana's (2000) model. They developed this approach in their study titled "An Examination of herd behavior in equity markets: An international perspectives" published in 2000. The major variation of this model from CH's model can be distinguised in that it is capable of detecting herding behavior not only in normal case but also in the condition of extreme market movements. The CCK model contends that rational asset pricing models presumes a linear relation between individual equity return dispersion and the return on market portfolio. The return dispersion will increase as the absolute value of market return changes. During periods of large average market price movements, market participants tend to chase the aggregate market trend by declining thier own evaluation. Thus, the linear relation between returns dispersion and the absolute value of market returns will no longer hold. Instead, the relation will become non-linear implying that dispersion among equity returns will decrease or at least increase at aless than proportional rate with the market return. CCK's empirical model to investigate herding behavior is built on this intution.

CCK model entrusts with a dispersion approach known as cross sectional absolute deviation to meausre the herding behavior and can be expressed as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \quad (6.6)$$

Where, $R_{i,t}$ is the observed stock return of security i at time t. $R_{m,t}$ is the cross-sectional average stock of N returns in the market portfolio at time t.

To develop a test for detecting herding behavior in the equity market, Change et al. (2000) specifies the following model:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{6.7}$$

Where, $CSAD_t$ is the measure of return dispersion. α is the constant component. $|R_{m,t}|$ is the absolute value of cross-sectional average stock of N returns in the market portfolio at time t. R_m^2 represents the squared aggregate market returns and captures the non-linear feature in the model. The negative and statistically significant value of the coefficient γ_2 would ensure the presence of herding behabvior.

The above model is constructed for the general market condition. To segregate the asymmetric response of herding behavior in case of positve and negative market chnages, we can formulate the following models:

$$CSAD_t^{Up} = \alpha + \gamma_1 |R_{m,t}^{Up}| + \gamma_2 R_{m,t}^{Up\,2} + \varepsilon_t \tag{6.8}$$

$$CSAD_t^{Down} = \alpha + \gamma_1 |R_{m,t}^{Down}| + \gamma_2 R_{m,t}^{Down^2} + \varepsilon_t \tag{6.9}$$

$|R_{m,t}^{Up}|$ ($|R_{m,t}^{Down}|$) is the absolute value of an equally weighted realized return of all availablessecurities on day t when the market is positive (negative). The presence of herding behavior to be detected by the statistically significant negative value of the coefficient γ_2.

Existing literature postulates that there is positive association between aggregate stock market returns and trading volume (Wermers, 1999; Nofsinger and Sias, 1999). Liu et al. (2017) observed positive correlation between stock returns of individual investors and average trading volumes. The study intends to examine whether investors herding behavior capture any possible asymmetric effects during periods of low or high trading volume. The trading volume is identified to be high (low) on day t if it is greater (lower) than last 30 days moving averages. The Chang et al. (2000) model is modified to separately estimate the herding behavior in high and low trading volume cases in the following ways:

$$CSAD_t^{V-High} = \alpha + \gamma_1^{V-High} |R_{m,t}^{V-High}| + \gamma_2^{V-High} \left(R_{m,t}^{V-High}\right)^2 + \varepsilon_t \tag{6.10}$$

$$CSAD_t^{V-Low} = \alpha + \gamma_1^{V-Low} |R_{m,t}^{V-Low}| + \gamma_2^{V-Low} \left(R_{m,t}^{V-Low}\right)^2 + \varepsilon_t \tag{6.11}$$

Where $R_{m,t}^{V-High}$ refers to aggregate market returns on day t when trading volume is high and $R_{m,t}^{V-Low}$ $i$ndicates market returns in low trading volume day. A statistically significant negative coefficients of γ_2 imply the presence of herding with respect to market trading volumes.

If investors behave irrationally, they follow the market movements by buying the securities when prices rise and selling when prices decline. This uninformed trading strategy will result in market volatility. Therefore, presence of volatility may lead to investor herd behavior. Similar to explanation of trading volume, we intend to examine any possible asymmetric herding effect during periods of high or low volatility. The volatility of daily returns is perceived to be high (low) on day t if it is greater (lower) than the last 30 days moving averages. In order to estimate the asymmetric herding behavior in volatility segments, the following specifications are developed:

$$CSAD_t^{Vol-High} = \alpha + \gamma_1^{Vol-High}\left|R_{m,t}^{Vol-High}\right| + \gamma_2^{vol-High}\left(R_{m,t}^{vol-High}\right)^2 + \varepsilon_t \quad (6.12)$$

$$CSAD_t^{vol-Low} = \alpha + \gamma_1^{Vol-Low}\left|R_{m,t}^{Vol-Low}\right| + \gamma_2^{Vol-Low}\left(R_{m,t}^{Vol-Low}\right)^2 + \varepsilon_t \quad (6.13)$$

Where, $R_{m,t}^{Vol-High}$ implies high market return volatility and $R_{m,t}^{Vol-Low}$presents low-return volatility, $\left(R_{m,t}^{vol-High}\right)^2$and $\left(R_{m,t}^{Vol-Low}\right)^2$ are the squared market return on corresponding high or low volatility days.

Instead of estimating asymmetric herding behavior separately for up and down markets in equations (6.8) and (6.9), we can follow a more robust approach proposed by Chiang et al. (2010) which considers a dummy variable in a single model:

$$CSAD_t = \alpha + \gamma_1 D\left|R_{m,t}\right| + \gamma_2(1-D)\left|R_{m,t}\right| + \gamma_3 D R_{m,t}^2 + \gamma_4(1-D)R_{m,t}^2 + \varepsilon_t \quad (6.14)$$

Where, D is the dummy variable that takes a value of 1 if market return on a particular day is positive; otherwise, equal to zero. If herding behavior exists, the coefficients of γ_3 and γ_4 should be negative and significant.

Instead of estimating equations (6.10), and (6.11), we can alternatively examine the potential asymmetric effects in herd behavior in relation to high and low market trading volume conditions adopting the dummy variables in a single model:

$$CSAD_t = \alpha + \gamma_1 D^{V-High}\left|R_{m,t}\right| + \gamma_2\left(1-D^{V-High}\right)\left|R_{m,t}\right| + \gamma_3 D^{V-High}R_{m,t}^2 + \gamma_4\left(1-D^{V-High}\right)R_{m,t}^2 + \varepsilon_t \quad (6.15)$$

Where, D^{V-High} is the dummy variable that takes a value of 1 if trading volume on a particular day is high; otherwise, equal to zero. The presence of herding behavior should be identified by the negative and significant coefficients of γ_3 andγ_4.

Instead of estimating equations (6.12), and (6.13), we can alternatively investigate whether any potential asymmetric herding behavior exists in relation to high and low market volatility conditions using the following dummy variable in a single model:

$$CSAD_t = \alpha + \gamma_1 D^{Vol-High}\left|R_{m,t}\right| + \gamma_2\left(1-D^{Vol-High}\right)\left|R_{m,t}\right| + \gamma_3 D^{Vol-High}R_{m,t}^2 + \gamma_4\left(1-D^{Vol-High}\right)R_{m,t}^2 + \varepsilon_t \quad (6.16)$$

Where, $D^{Vol-High}$ is the dummy variable that takes a value of 1 if market volatility on a particular day is high; otherwise, equal to zero.

To investigate robustness of trading volume effects on herding behavior, we estimate the following models during periods of abnormal high and low trading volume using dummy variables.

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{V-Abn\,High} R_{m,t}^2 + \gamma_4 D^{V-Abn\,Low} R_{m,t}^2 + \varepsilon_t \qquad (6.17)$$

Where, $D^{V-Abn\,High}$ is the dummy variable takes a value 1 if market trading volume on day t lies in the extreme upper tail of the trading volume distributions; and zero otherwise. $D^{V-Abn\,Low}$ is the dummy variable that takes a value 1 if market trading volume on day t lies in the extreme lower tail of the trading volume distributions; and zero otherwise. We estimate equation (6.17) using 1%, and 5% of the observations in the upper and lower tail of the trading volume distribution as our definition of abnormal high and low trading volume.

Similarly, to test robustness of market volatility effects on herding behavior, we estimate the following models during periods of abnormal high and low market volatility using dummy variables

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{Vol-Abn\,High} R_{m,t}^2 + \gamma_4 D^{Vol-Abn\,Low} R_{m,t}^2 + \varepsilon_t \qquad (6.18)$$

Where, $D^{Vol-Abn\,High}$ is the dummy variable that takes a value 1 if market volatility on day t lies in the extreme upper tail of the volatility distributions; and zero otherwise. $D^{Vol-Abn\,Low}$ is the dummy variable that takes a value 1 if market volatility on day t lies in the extreme lower tail of the volatility distributions; and zero otherwise. We estimate equation (6.18) using 1%, and 5% of the observations in the upper and lower tail of the volatility distribution as our definition of abnormal high and low market volatility.

To test the robustness of regression models employed to investigate the relationship between equity return dispersion and market return, we modify the baseline equation in following way:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 V_{m,t} + \varepsilon_t \qquad (6.19)$$

Where, $V_{m,t}$ is the log of equally weighted market trading volume on day t. We include market trading volume in the model as a control variable to justify the robustness of the model.

In addition to CSAD as a measure of return dispersion, we modify the general form of the Chang et al., (2000) model to investigate herding behavior using Christie & Huang's (1995) measure of CSSD, which does not require estimation of CAPM (Chiang & Zheng, 2010; Gleason et al., 2004; Hwang & Salmon, 2004; Tan et al., 2008; Yao et al., 2014). This research contributes to the existing literature in that we alternatively investigated herding behavior using both return dispersion measures (CSAD and CSSD). The model specification of cross-sectional standard deviation (CSSD) looks like:

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad (6.20)$$

Finally, the high frequency time series return data may reflect a high level of serial correlation. Any failure to properly accommodate this issue will result in biased estimates of regression parameters. We employ a 1-day lag of dependent variable as a regressor in our all-estimated equations to further improve the power of regression model and can be expressed as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 CSAD_{t-1} + \varepsilon_t \quad (6.21)$$

The essay further investigates how the macroeconomic variables can induce herding tendency of investors. The macro-based models are specified as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta exr+} R_{m,t}^2 + \varepsilon_t \quad (6.22)$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta exr-} R_{m,t}^2 + \varepsilon_t \quad (6.23)$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta int+} R_{m,t}^2 + \varepsilon_t \quad (6.24)$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta int-} R_{m,t}^2 + \varepsilon_t \quad (6.25)$$

Where, $|R_{m,t}|$ represents represent the absolute value of the equally weighted market returns, calculated using the returns of all listed securities on day t, $R_{m,t}^2$ represents the market returns square. The $D_1^{\Delta exr+}$ represents a dummy variable that takes value one when the local currency (BDT) depreciates (exchange rate increases) and zero otherwise; The $D_2^{\Delta exr-}$ represents a dummy variable that takes value one when the local currency appreciates (exchange rate decreases) and zero otherwise; The $D_1^{\Delta int+}$ represents a dummy variable that takes value one when the interest rates increase and zero otherwise; the $D_2^{\Delta int-}$ represents a dummy variable that takes value one when the interest rates decrease and zero otherwise. We employ a repo rate as a measure of interest rate. The coefficients γ_3 and γ_4 should be negatively significant to confirm herding behavior.

The study also examines how the effect of monetary policy influences the herding effects among investors in the Bangladesh equity market. The models are specified as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varphi_j D_j R_{m,t}^2 + \varepsilon_t \qquad (j=1,2,3,4,5) \quad (6.26)$$

Where, $|R_{m,t}|$ represents the absolute value of the equally weighted market returns, calculated using the returns of all listed securities on day t, $R_{m,t}^2$ represents the market returns squared. D_1 to D_4 represent dummy variables that take value one in a month when the deposit rate increases, the deposit rate decreases, the deposit reserve ratio increases, and the deposit reserve ratio decreases, respectively and zero otherwise. D_5 represents a dummy variable that takes value one during monetary policy announcement month and zero otherwise. The coefficients φ_1 through φ_5 should be negatively significant when monetary policy tools have an impact on herding behavior.

6.7.2.2 Quantile Regression

Quantile regression model can be used to estimate the coefficients as a conditional quantile of a response variable given the different predictor variable. Quantile regression is the semi-parametric technique introduced by Koenkar & Bassett (1978) to adequately capture the non-linear relationship between dependent and independent variables. It attempts to provide a detailed characterization of the data set by estimating differential impact of covariates on the entire conditional distribution of response variable (Ababio & Mwamba, 2017; Buchinsky, 1998). It also provides a more comprehensive framework for modeling the relationship between dependent and independent variables across different quantiles of the data, giving a more insight into how predictors influence the various segments of the distribution.

The general model specification of quantile regression is as follows:

$$Q_\tau(Y|X) = X\beta_\tau \tag{6.27}$$

Where, $Q_\tau(Y|X)$ is the τ th conditional quantile of the response variable Y given the predictor variables X

X is the matrix of predictor variables

β_τ is the vector of coefficients for quantile regression.

Quantile regression minimizes a weighted sum of positive and negative error terms with the following function:

$$Q(\beta_q) = \tau \sum_{y_i > \hat{\beta}'_\tau X_i} \left| y_i - \hat{\beta}'_\tau X_i \right| + (1-\tau) \sum_{y_i < \hat{\beta}'_\tau X_i} \left| y_i - \hat{\beta}'_\tau X_i \right| \tag{6.28}$$

Where, τ is the quantile level.

To investigate the relation between equity return dispersion and market return, we can formulate the following quantile regression:

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau}(R_{m,t})^2 + \varepsilon_t \tag{6.29}$$

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}|R_{m,t}{}^{Up}| + \gamma_{2,\tau}(R_{m,t}{}^{Up})^2 + \varepsilon_t \tag{6.30}$$

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}|R_{m,t}{}^{Down}| + \gamma_{2,\tau}(R_{m,t}{}^{Down})^2 + \varepsilon_t \tag{6.31}$$

Where, X_t is a vector of the right-hand side variables in equation 6.29 through 6.31. The equations 6.30 and 6.31 are estimated to examine herding behavior in upward and downward market conditions. If herding behavior exists, $\gamma_{2,\tau}$ coefficient should be statistically negative.

To examine herding behavior in high (low) trading volume, and high (low) market volatility conditions, the following quantile regression models can be developed:

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}|R_{m,t}{}^{V-High}| + \gamma_{2,\tau}(R_{m,t}{}^{V-High})^2 + \varepsilon_t \tag{6.32}$$

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}\left|R_{m,t}{}^{V-Low}\right| + \gamma_{2,\tau}\left(R_{m,t}{}^{V-Low}\right)^2 + \varepsilon_t \quad (6.33)$$

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}\left|R_{m,t}{}^{Vol-High}\right| + \gamma_{2,\tau}\left(R_{m,t}{}^{Vol-High}\right)^2 + \varepsilon_t \quad (6.34)$$

$$Q_r(\tau|X_t) = \alpha + \gamma_{1,\tau}\left|R_{m,t}{}^{Vol-Low}\right| + \gamma_{2,\tau}\left(R_{m,t}{}^{Vol-Low}\right)^2 + \varepsilon_t \quad (6.35)$$

Where, X_t is a vector of the right-hand side variables in equation 6.32 through 6.35. The equations are estimated to examine herding behavior in high (low) trading volume, and high (low) market volatility conditions, respectively. If the results show evidence of herding behavior, $\gamma_{2,\tau}$ coefficient in these equations is expected to be significant and negative.

Given the complex nature of high frequency time series data, applying quantile regression alongside OLS can offer more robust outcomes to handle the outliers. It can also capture more effectively the non-linear relationships between independent and dependent variables. Another benefit of using quantile regression over OLS is that former estimates how independent variables influence different quantiles of the dependent variable’s distribution exploring a better modeling to understand the relationship between variables.

6.8 Empirical Findings

Christie & Huang (1995) define herding behavior as “investors who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions”. In this chapter, we delineate the results of empirical analysis on herding behavior among market participants in the Bangladeshi equity market. The chapter commences with an overview of descriptive statistics and stationarity tests to understand the nature of the data characteristics. Subsequently, we will demonstrate the interpretation of various empirical methodologies employed in this research to provide insights into the dynamics of herding tendencies of market participants in our equity market. Finally, this chapter will provide a comprehensive understanding of the potential avenues for future research and the practical policy implications of market functioning in the context of Bangladesh equity market.

6.8.1 Descriptive Statistics

Table 6.6 provides a summary of univariate descriptive statistics for daily market returns, the cross-sectional standard deviation (CSSD), and cross-sectional absolute deviation (CSAD) of returns. The average daily returns range from a low of -36.78% to a high of 40.285 for the whole study period. The mean daily return for the whole period is -0.0585. The lowest mean return is characterized by extended crisis period with -0.38%, whereas the highest mean return has been identified as 0.1073% during the COVID-19 pandemic. The market return volatility is also highest for extended crisis period with standard deviation of 2.38% and the lowest value is 0.389% for the same period. Among the different sub-periods, the largest return declined of -36.78% occurred for extended crisis and bearish periods and the highest return gain of 4.28% happened in crisis, extended crisis, and bearish periods.

Table 6.6: Summary Statistics of market return ($R_{m,t}$), cross-sectional standard deviation ($CSSD_t$), and cross-sectional absolute deviation ($CSAD_t$)

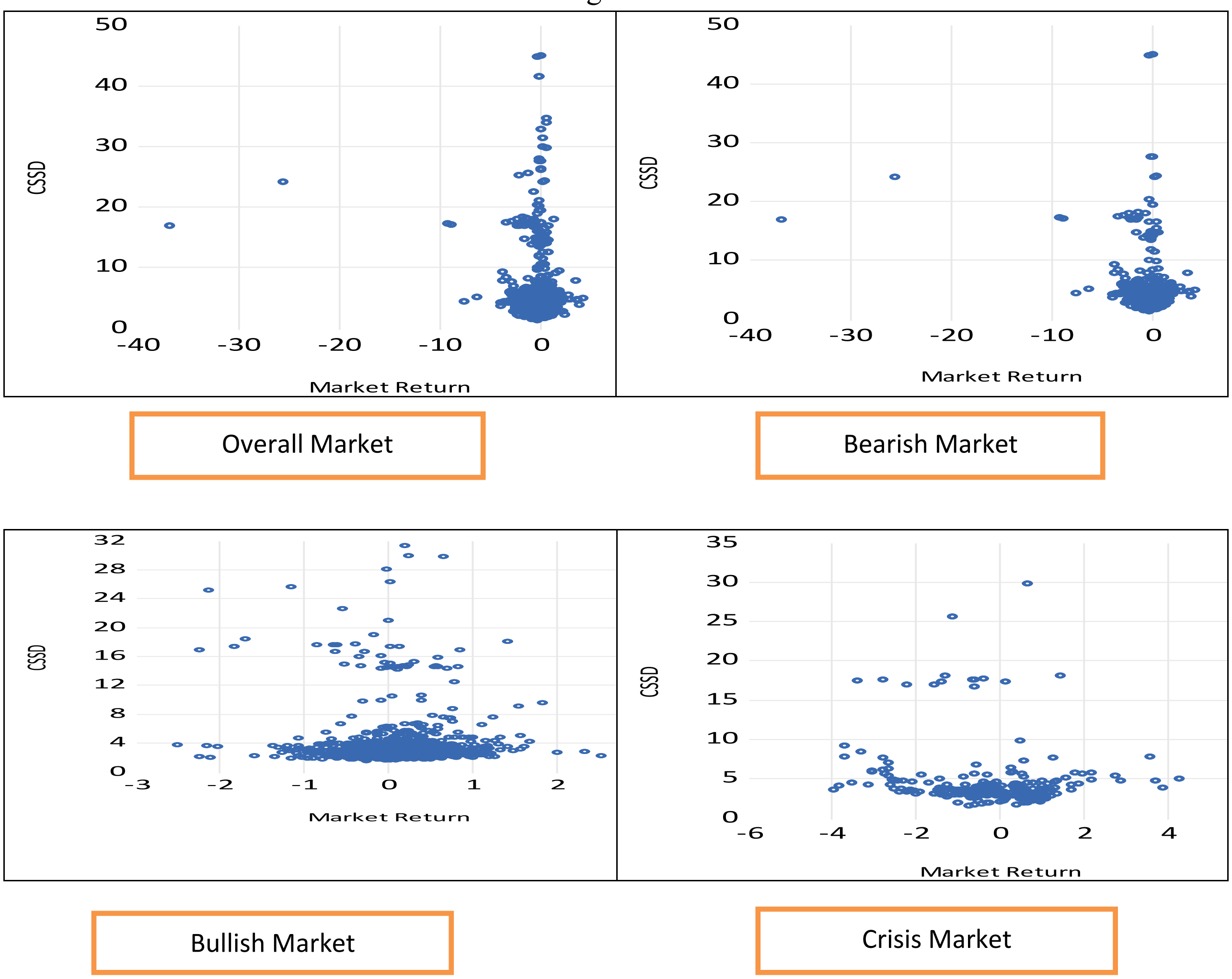
This table reports the descriptive statistics of daily market returns ($R_{m,t}$), daily cross-sectional standard deviation (CSSD), and daily cross-sectional absolute deviation (CSAD) for overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

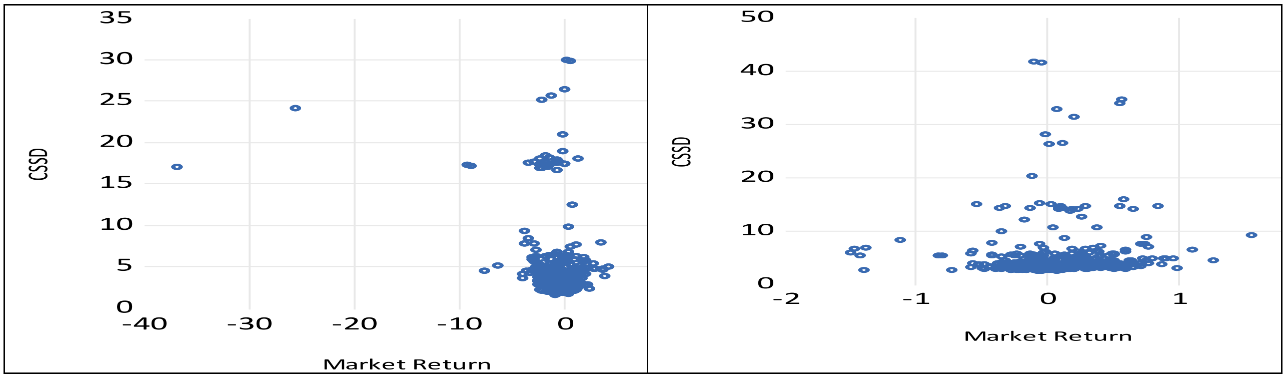
Variable	Mean (%)	SD (%)	Minimum	Maximum	Skewness	Kurtosis
Overall Market						
$R_{m,t}$	-0.0858	1.120	-36.78	4.280	-17.11	501.43
$CSSD_t$	3.7243	3.5231	1.3369	45.036	5.5801	40.509
$CSAD_t$	1.9286	1.0523	0.74268	36.784	18.030	530.59
Crisis						
$R_{m,t}$	-0.25031	1.4134	-3.9550	4.2804	-0.16993	0.6200
$CSSD_t$	4.7030	3.8956	1.5915	29.859	3.5533	13.849
$CSAD_t$	2.2789	0.9662	0.9141	6.0163	1.3556	1.8863
Extended Crisis Market						
$R_{m,t}$	-0.38002	2.3820	-36.780	4.280	-9.1336	124.02
$CSSD_t$	4.4595	4.0831	1.5915	30.006	3.5854	13.496
$CSAD_t$	2.2278	2.1021	0.85935	36.784	11.526	169.06
Bearish Crisis Market						
$R_{m,t}$	-0.23732	1.4501	-36.780	4.2800	-14.628	330.26
$CSSD_t$	3.5568	3.1099	1.3369	45.036	6.2718	55.542
$CSAD_t$	1.9824	1.3230	0.74268	36.784	16.920	397.92
Bullish Market						
$R_{m,t}$	0.08392	0.52872	-2.5100	2.5400	-0.29730	2.9246
$CSSD_t$	3.6457	3.3542	1.6271	31.370	4.5668	24.084
$CSAD_t$	1.7653	0.59458	0.85935	5.7788	2.0061	6.4995
Covid-19 Market						
$R_{m,t}$	0.10729	0.38908	-1.4957	1.8320	-0.32641	3.3108
$CSSD_t$	5.3020	5.0782	2.4059	41.649	4.3827	22.318
$CSAD_t$	2.5228	0.64437	1.6223	6.1473	2.2525	6.9671

Table 6.6 also reports the univariate statistics on the CSSD and CSAD variables for the whole sample as well as for the different sub-markets' classification. In rational behavior, security returns dispersion moves with the absolute value of market returns. If investors tend to follow market movements, individual security returns tend to converge on the market return, and the value of cross-sectional return dispersion decreases. The average daily CSSD for the whole sample ranges from a low of 1.33% to a high of 45.03%. On the other hand, the CSAD is identified from a lowest value of 0.74% to the highest value of 36.78%. Within the framework of

market classifications, both the lowest and highest CSSD value of 1.33% and 45% are observed in case of bearish period. It implies that stock returns significantly move from the market return on a trading day in both directions during the bearish phase of the market. However, bearish period has also confirmed the minimum and maximum CSAD, which are 0.74% and 36.78%, respectively. In comparison between these two return dispersion measures, it is observed that the daily mean and variability is lower for CSSD relative to CSAD measure.

Figure 6.2 depicts the relationship between market return and cross-sectional standard deviation (CSSD) for each of the market classifications. Looking at the graph, we can observe a positive relationship between the aggregate market return and CSSD for all market conditions, with the dispersion being more prominent for bullish and crisis markets. Figure 6.3 describes the relationship between cross-sectional absolute deviation (CSAD) and market return and enables us to draw the similar conclusions made for Figure-6.2.

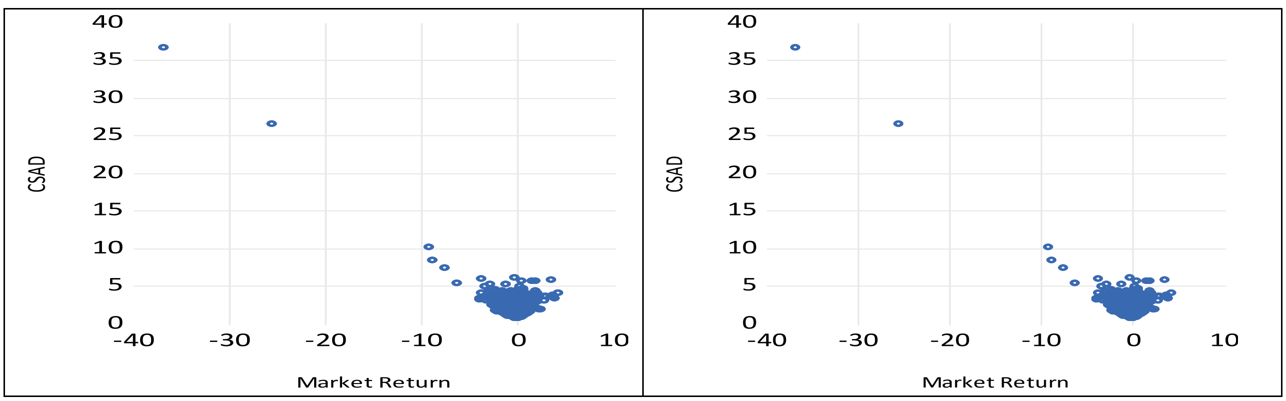




Extended Crisis Market

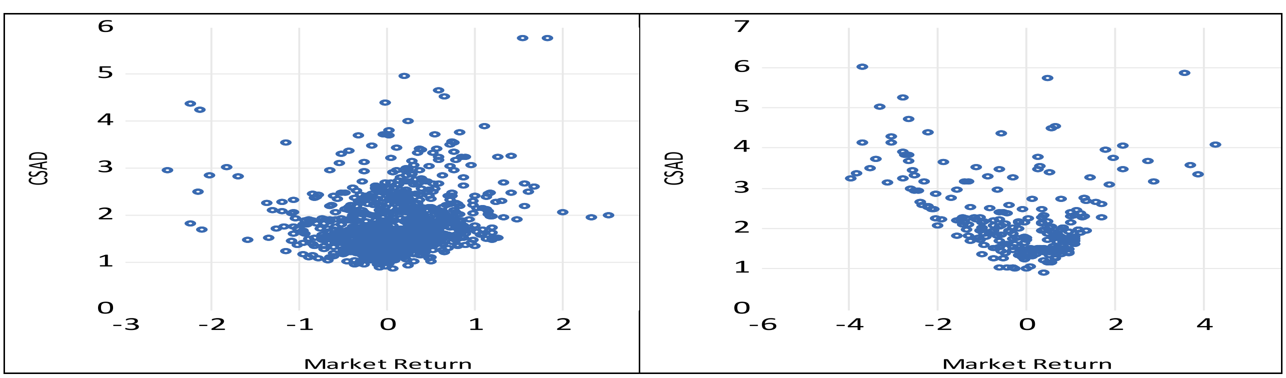
COVID-19 Market

Figure 6.2: Relationship between CSSD and market return



Overall Market

Bearish Market



Bullish Market

Crisis Market

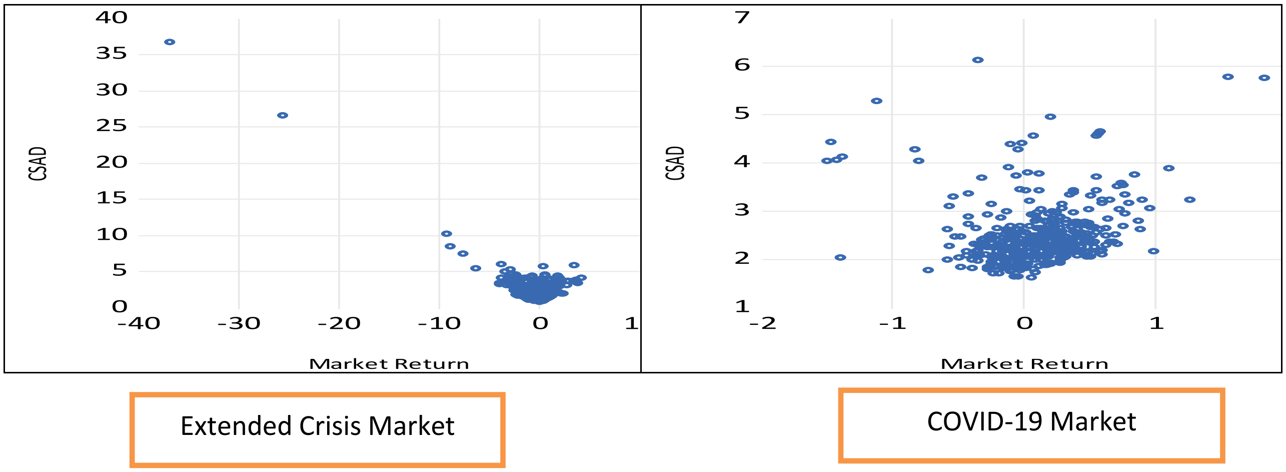


Figure 6.3: Relationship between CSAD and market return

6.8.3 Unit Root for Testing Nonstationarity

Time series data normally assumes that underlying time series are stationary before we estimate any regression model. However, the series in finance may exhibit non-stationary and using this series may produce biased regression outcome and also result in a non-constant mean over time (Kutty, 2010). Therefore, all variables, cross-sectional standard deviation (CSSD), cross-sectional absolute deviation (CSAD), and market return are tested for unit roots applying the Augmented Dickey and Fuller (ADF) and Phillip-Perron (PP) Tests.

Table 6.7: Results of unit root tests

Table reports the results of unit root tests of cross-sectional standard deviation (CSSD), cross-sectional absolute deviation (CSAD), and R_m an equally-weighted realized retrun of all available securities on day t included in the market portfolio (R_m) for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 – December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

Variable	Augmented Dickey and Fuller (ADF)		Phillip-Perron(PP)	
	Test Statistic	P-Value	Test Statistic	P-Value
Overall Market Period				
CSSD	-16.278	0.000***	-36.953	0.000***
CSAD	-13.275	0.000***	-22.682	0.000***
R_m	-17.74	0.000***	-22.51	0.000***
Bearish Market Period				
CSSD	-17.47	0.000***	-23.90	0.000***
CSAD	-9.05	0.000***	-15.52	0.000***
R_m	-11.88	0.000***	-14.67	0.000***
Bullish Market Period				
CSSD	-10.95	0.000***	-23.25	0.000***

CSAD	-3.51	0.000***	-15.12	0.000***
R_m	-21.15	0.000***	22.58	0.000***
Crisis Market Period				
CSSD	-3.50	0.000***	-4.96	0.000***
CSAD	-5.20	0.000***	-12.85	0.000***
R_m	-8.13	0.000***	-8.15	0.000***
Extended Crisis Market Period				
CSSD	-11.36	0.000***	-17.18	0.000***
CSAD	-8.99	0.000***	-9.60	0.000***
R_m	-10.99	0.000***	-9.99	0.000***
Covid-19 Market Period				
CSSD	-9.21	0.000***	-11.56	0.000***
CSAD	-6.69	0.000***	-9.07	0.000***
R_m	-6.54	0.000***	-12.77	0.000***
: ***The coefficient is significant at the 1% level				

The results of unit roots test are presented in Table 6.7 and indicate that all variables for all market classifications are free of unit roots as the null hypothesis of unit root has been rejected at 1% level both Augmented Dickey and Fuller (ADF) and Phillip-Peron tests. Thus, all series of CSSD, CSAD, and R_m are stationary at level form and can be used for model estimation purposes.

6.8.4 Cross-sectional standard deviation (CSAD) Regression Results during Extreme Market Movements

This section starts with the investigation of the presence of the herding behavior by employing the cross-sectional standard deviation regression under extreme market conditions. The coefficients dummy variables capture whether herding behavior present during the trading days with extreme up and down markets. In this research, we estimate the equation (6.5) at 1% and 5% criteria for the lower and upper tail of the market return distributions as our definition of extreme market movements. In Table 6.8, we report the parameter estimates of CSAD and CSSD regression.

The coefficient of γ_2 is positive and statistically significant for the overall stock market as well as for bearish, bullish, crisis, and extended crisis periods for cross-sectional standard deviation model. The coefficient of γ_1 is not statistically significant for any of the period. Neither of the coefficients are found significant for the COVID-19 pandemic period. Similar results we found in case of cross-sectional absolute deviation model except that the coefficient of γ_1 is now significant for overall, bullish and crisis period. The adjusted R^2 value is significantly higher in all estimated periods for CSAD model. The high adjusted R^2 value notably confirms the more explanatory power to the CSAD model compared to CSSD model. Findings indicate that equity return dispersions tend to increase rather than decrease during extreme price movements, in other words, no herding behavior exists supporting the assumption of rational asset pricing. Rational asset pricing model states that individual stocks return dispersions increase with the level of market return during market stress period because of their sensitivity to the aggregate market. Whereas equity return dispersion tend to increase at a decrease rate in case of herding.

Table 6.8: Regression results under extreme market movements at 5% Criterion using dummy variable

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t = \alpha + \gamma_1 D_t^U + \gamma_2 D_t^D + \varepsilon_t$$
$$CSAD_t = \alpha + \gamma_1 D_t^U + \gamma_2 D_t^D + \varepsilon_t$$

Where D_t^U and D_t^D equals 1 if market return on day t lies in the extreme upper and lower tail of the market return distributions, otherwise D_t^U and D_t^D becomes0. The 5% criterion is used as the percentage of the observations in the upper and lower tail of the distribution to define the extreme market conditions. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	CSSD Model			**CSAD Model**		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	3.624***	0.034	1.955***	0.528***	0.239***	0.668***
	(18.39)	(0.067	(8.54)	(19.36)	(3.97)	(10.85)
	Adj. R^2=0.2180			Adj. R^2=0.5668		
Bearish Market	3.399***	0.097	1.874***	1.932***	0.265	0.508***
	(15.03)	(0.11)	(8.56)	(10.47)	(0.92)	(3.41)
	Adj. R^2=0.2281			Adj. R^2=0.5415		
Bullish Market	3.589***	0.189	3.072***	1.739***	0.282***	0.736***
	(11.14)	(0.37)	(7.90)	(25.03)	(8.10)	(18.54)
	Adj. R^2=0.2075			Adj. R^2=0.6195		
Crisis Market	4.254***	0.245	1.827***	2.075***	0.299***	0.620***
	(5.35)	(0.25)	(2.83)	(9.86)	(3.02)	(8.33)
	Adj. R^2=0.0697			Adj. R^2=0.6983		
Extended Crisis Market	4.000***	-0.107	2.280***	2.037***	0.263	0.685
	(7.03)	(-0.13)	(5.76)	(3.92)	(0.43)	(1.76)
	Adj. R^2=0.1621			Adj. R^2=0.5027		
COVID-19 Market	5.305***	-0.257	-0.076	2.526***	0.097	-0.025
	(6.24)	(-0.04)	(-0.00)	(22.55)	(0.44)	(-0.18)
	Adj. R^2=0.2170			Adj. R^2=0.5375		

Note: ***The coefficient is significant at 1% level. The t-statistics are reported in parentheses.

Table 6.9 reports the results estimated from both CSSD and CSAD models when 1% cut off criterion is used to represent the extreme market movements. The findings are similar to the Table 6.8 presented under 5% market criterion indicating a divergence of individual stock returns from the overall market returns, in other words confirms the absence of herding behavior in Bangladesh stock market under market stress. We conclude the statistically positive sign of both dummy variables, which are the herding coefficients, under CSSD and CSAD models describes that equity return dispersion tends to increase at an increasing rate. This finding is against the theoretical assumption of original Christie & Huang (1995) model in which investors tend to be aligned with the average collective market behavior during market turmoil periods. In comparison between CSSD and CSAD models estimation under extreme market conditions, CSAD provides a better fit to the dataset. Our result is consistent with the findings of (Ahsan and Sarkar, 2013, Huang et al., 2015; Sharma, 2018).

Table 6.9: Regression results under extreme market movements at 1% Criterion using dummy variable

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t = \alpha + \gamma_1 D_t^U + \gamma_2 D_t^D + \varepsilon_t$$
$$CSAD_t = \alpha + \gamma_1 D_t^U + \gamma_2 D_t^D + \varepsilon_t$$

Where, D_t^U and D_t^D equals 1 if market return on day t lies in the extreme upper and lower tail of the market return distributions, otherwise D_t^U and D_t^D becomes0. The 1% criterion is used as the percentage of the observations in the upper and lower tail of the distribution to define the extreme market conditions. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	CSSD			**CSAD**		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	3.712***	-0.245	2.671***	0.617***	0.419***	1.916***
	(18.44)	(-0.202)	(5.95)	(21.94)	(3.18)	(13.63)
	Adj. R^2=0.2116			Adj. R^2=0.5759		
Bearish Market	3.506***	0.056	2.842***	1.955***	0.382	1.471***
	(16.40)	(0.052)	(8.50)	(12.59)	(1.33)	(10.97)
	Adj. R^2=0.2187			Adj. R^2=0.5462		
Bullish Market	3.102***	0.178`	3.210***	2.891***	0.1634***	0.98***
	(12.34)	(1.24)	(7.24)	(7.24)	(2.78)	(9.32)
	Adj. R^2=0.2232			Adj. R^2=0.6021		
Crisis Market	4.494***	0.183	2.466***	2.201***	0.272**	0.587***
	(6.34)	(0.048)	(2.87)	(12.06)	(2.05)	(4.67)
	Adj. R^2=0.0607			Adj. R^2=0.6342		
Extended Crisis Market	4.307***	-0.279	3.196***	2.126***	0.375	1.607***
	(8.06)	(-0.127)	(4.95)	(5.12)	(0.524)	(4.37)
	Adj. R^2=0.1398			Adj. R^2=0.5044		

COVID-19 Market	5.021***	-0.312	-0.071	2.322***	0.091	-0.029
	(8.21)	(-0.09)	(-0.02)	(17.22)	(0.54)	(-0.28)
	Adj. R^2=0.22.65			Adj. R^2=0.56.21		

Note: ***The coefficient is significant at 1% level.
**The coefficient is significant at 5% level. The t-statistics are reported in parentheses.

The herding effect during the extreme market conditions can also be examined by using the magnitude of market return at its tail distributions in a non-linear fashion specified in equation 6.5.

Table 6.10: Regression results of CSSD under extreme market movements using the modified dummy variable model

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t = \alpha + \gamma_1 D_t^U |R_{m,t}| + \gamma_2 D_t^D |R_{m,t}| + \gamma_3 D_t^U R_{m,t}^2 + \gamma_4 D_t^D R_{m,t}^2 + \varepsilon_t$$

Where, D_t^U takes a value of 1 if the returns of the market on day t lies in the extreme upper tail of the return distributions; and zero otherwise, and D_t^D takes a value of 0 if the returns of the market on day t lies in the extreme lower tail of the distributions; and zero otherwise. The 5% criterion is used as the percentage of the observations in the upper and lower tail of the distribution to define the extreme market conditions. $|R_{m,t}|$ is the absolute value of an equally-weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. In order to detect herding behavior, the coefficients γ_3 and γ_4 should be negatively significant. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 – December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

Regression results at 5% extreme market movements

	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Overall Market	3.60***	0.024	1.12***	0.030	**-0.022*** **	0.224
	(18.7)	(0.02)	(12.43)	(0.06)	**(5.77)**	
Bearish Market	3.35***	0.08	1.08***	0.015	**-0.021*** **	0.244
	(16.0)	(0.07)	(14.02)	(0.03)	**(7.09)**	
Bullish Market	3.58***	-0.332	0.214	0.427	0.869	0.211
	(11.7)	(-0.15)	(0.13)	(0.30)	(1.18)	
Crisis Market	4.21***	0.252	1.31	-0.007	-0.188	0.064
	(5.33)	(0.17)	(1.68)	(-0.01)	(-0.76)	
Extended Crisis Market	3.90***	-0.174	1.14***	0.091	**-0.022*** **	0.292
	(7.34)	(-0.13)	(7.63)	(0.13)	**(3.42)**	
COVID-19 Market	5.29***	-3.03	0.436	2.43	-0.340	0.214
	(6.24)	(-0.11)	(0.00)	(0.09)	(-0.00)	

Note: ***The coefficient is significant at 1% level. The t-statistics are reported in parentheses

Table 6.10 states the regression results of the impact of the magnitude of market return at its tail distribution upon cross-sectional standard deviation (CSSD) with AR=1 model. The results clearly demonstrate that the coefficient γ_4 is statistically significant and negative for the entire market, bearish, and extended crisis periods at both 5% criterion. It confirms that investors in Bangladesh equity market avoid their own private analysis and tend to follow the aggregate market movements during extreme down-market movements. Since both 5% and 1% criteria generate similar results, we report only the results from 5% criterion. It may be argued that fear and panic motive investors to replicate the others' decision when market experiences a large downward price movement.

6.8.5 Examining the non-linearity in the Cross-sectional absolute deviation (CSAD) and Cross-sectional standard deviation (CSSD)-Market Return Nexus

We start the analysis of basic non-linear specification of cross-sectional absolute deviation (CSAD) of Chang et al. (2000) in equation 6.7 to measure the tendency of herd behavior among investors in Bangladesh equity market. Table 6.11 provides the regression results based on CSAD model, where the non-linear term is included in the model with the coefficient of market return square.

Table 6.11: Regression results of the non-linear daily cross-sectional absolute deviation (CSAD) model

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

Where, $|R_{m,t}|$ is the absolute value of an equally weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. The negative and statistically significant value of the coefficient γ_2 would ensure the presence of herding behabvior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	α	γ_1	γ_2	Adj. R^2	F-Stat
Overall Market	1.723***	0.378***	0.013***	0.889	(570.)***
	(35.04)	(64.98)	(85.27)		
Bearish Market	1.752***	0.331***	0.012***	0.933	(425)***
	(23.47)	(38.08)	(74.48)		
Bullish Market	1.641***	0.175***	0.189***	0.663	(432)***
	(22.93)	(3.05)	(7.07)		
Crisis Market	1.808***	0.520***	**-0.059****	0.725	(126)***
	(8.44)	(5.05)	**(-2.20)**		
Extended Crisis Market	1.660***	0.411***	0.010***	0.941	(169)***
	(14.03)	(19.82)	(26.04)		

COVID-19 Market	2.461***	0.078	0.148	0.556	(100)***
	(22.98)	(0.493)	(1.153)		

Note: ***The coefficient is significant at 1% level.
**The coefficient is significant at 5% level. The t-statistics are reported in parentheses.

The α value in the regression measures the equity return dispersions in a stagnant condition where market return is equal to zero. This value ranges from a high of 2.46 in the COVID-19 period to a low of 1.64 in bullish market period. We find that the coefficient on the linear term of absolute market return is positive and statistically significant for the whole study period and for each of the market period classified in the study except COVID-19. For all periods of market classification, this result strongly confirms the prediction of rational asset pricing model that CSAD increases with the absolute market value. The coefficient of market return square, which is non-linear term, is statistically positive for the entire market, bearish, bullish, and extended crisis period but not significant for the COVID-19. The positive significant coefficient of non-linear market return indicates the finding of equity return dispersions increase at an increasing rate, does not coincide with the prediction of rational asset pricing model in Bangladesh equity market. Thus, the linear relation between CSAD and market return clearly does not hold as built in our intuition of the empirical models. However, for the crisis period, we find statistically significant negative coefficient of non-linear term. This suggests evidence of herding behavior in Bangladesh equity market only for the crisis period. Investors, in the crisis time, imitate the actions carried out by others in the market to a greater extent by sacrificing their own information and knowledge. The findings support study of (Khan & Imam, 2023) for the existence of herding behavior in Bangladesh equity market. The presence of herding during crisis period is also supported by the studies of Economou et al., (2013); Liu et al., (2017); Litimi, (2017); Ouarda et al., (2013); Shah et al., (2017).

Table 6.12: Regression results of the non-linear daily cross-sectional standard deviation (CSSD) model

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

Where, $\left|R_{m,t}\right|$ is the absolute value of an equally weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. The negative and statistically significant value of the coefficient γ_2 would ensure the presence of herding behabvior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	A	γ_1	γ_2	Adj. R^2	F-Stat
Overall Market	3.333***	0.828***	**-0.015*** **	0.222	(200)***

	(16.43)	(9.19)	**(-4.70)**		
Bearish Market	3.095***	0.697***	**-0.020*****	0.240	(96)***
	(13.66)	(3.29)	**(-6.95)**		
Bullish Market	3.539***	-0.217	0.796***	0.213	(60)***
	(9.88)	(-0.39)	(2.90)		
Crisis Market	3.557***	1.416	-0.236	0.081	(5.21)***
	(3.94)	(1.51)	(-0.914)		
Extended Crisis Market	3.587***	0.716***	**-0.025*****	0.196	(27.2)***
	(6.26)	(2.52)	**(-3.40)**		
COVID-19 Market	5.541***	-1.739	1.334	0.217	(23.5)***
	(6.41)	(-0.61)	(0.34)		

Note: ***The coefficient is significant at 1% level. The t-statistics are reported in parentheses.

Table 6.12 presents the results of regression estimated using equation 6.7 where we substitute cross-sectional standard deviation instead of cross-sectional absolute deviation to test the herding behavior. The coefficient $\gamma_1$is significantly positive for whole period, bearish and extended crisis period which strongly support the relation that CSSD increases with the absolute value of market return. The rate of change is significantly higher in each case compared to the change found in CSAD model. But it is not statistically significant for other periods contradicting the assumption of rational asset pricing behavior. The coefficient of $\gamma_2$is statistically significant and negative for the whole market period, bearish and extended crisis period. This negatively significant coefficient is inevitable for the operational definition of herding behavior. The results suggest that individual investors suppress their own beliefs and follow the market consensus. In case of CSSD model, we find herding behavior for the entire market, bearish market period, and extended market period that was not present in CSAD model, which affirms that former model of CSSD is more intensive to capture the inventors' imitating behavior relative to CSAD model originally developed by Change et al. (2000). This is a new finding we document in the herding behavior literature not yet explored in any other study.

6.8.6 Robustness Test

We perform a robustness test to examine the non-linearity in the cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD)-market return nexus. The objective is to verify our findings by re-estimating equation 6.7 with the inclusion of market trading volume as a control variable in the model.

Table 6.13: Robustness test results of non-linear CSAD and CSSD model

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \gamma_3 V_{m,t} + \varepsilon_t$$

$$CSSD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \gamma_3 V_{m,t} + \varepsilon_t$$

Where, $V_{m,t}$ is the log of equally-weighted market trading volume on day t, $\left| R_{m,t} \right|$ is the absolute value of an equally-weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. The negative and statistically significant value of the coefficient γ_2 would ensure the presence of herding behabvior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010-

June 2011), extended crisis (September 2009-April 2012), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	CSAD			CSSD		
	γ_1	γ_2	γ_3	γ_1	γ_2	γ_3
Overall Market	0.384***	0.013***	-0.001	0.891***	**-0.017*** **	0.019
	(0.000)	(0.000)	0.528	(0.000)	**(0.000)**	0.180
Bearish Market	0.367***	0.013***	-0.135**	0.898***	**-0.016*** **	0.424
	(0.000)	(0.000)	0.045	(0.000)	**(0.000)**	0.449
Bullish Market	0.181***	0.185***	-0.007	-0.485	0.939***	0.292
	(0.000)	(0.000)	0.916	0.378	(0.000)	0.465
Crisis Market	0.559***	**-0.067** **	-0.011	1.43	-0.128	0.159
	(0.000)	**0.016**	0.413	0.132	0.623	0.128
Extended Crisis Market	0.456***	0.011***	-0.156	1.14***	**-0.021*** **	1.89**
	(0.000)	(0.000)	0.245	(0.000)	**(0.000)**	0.029
COVID-19 Market	0.162	0.100	-0.001	2.07	1.51	-0.124***
	0.433	0.482	0.976	0.472	0.636	(0.000)

Note: ***The coefficient is significant at the 1% level.
**The coefficient is significant at the 5% level. The p-value is reported in parentheses.

The results from Table 6.13 manifest that under CSAD, the coefficient of non-linear term is negatively significant only for the crisis market, while under CSSD, herding coefficient is negative and significant for the overall, bearish, and extended crisis markets. This evidence strongly supports our findings reported in Table 6.11 and 6.12. We may conclude that our regression estimations provide more robust and reliable empirical evidence regarding herding behavior among market participants in the Bangladesh equity market.

6.8.7 Examining Asymmetric Effect of Herding Behavior under different Market Conditions: Up and Down Markets

The behavior of investors in equity market may represent asymmetric pattern depending on the different market conditions. It is hypothesized that more herding may be observed during the falling market days as compared to rising market days. This happens because there is a psychological implication for the moments of declining prices as opposed to the moments in which market observes a positive price change. The direction of market return (up or down) may affect investors' herding tendency differently (Chang et al., 2000, Demirer & Kutan, 2006). Table 6.14 provides the results estimated using equations 6.8 and 6.9 separately for cross-sectional absolute deviation measure.

Table 6.14: Regression results of CSAD measure in up and down market

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t^{Up} = \alpha + \gamma_1 \left|R_{m,t}^{Up}\right| + \gamma_2 {R_{m,t}^{Up}}^2 + \varepsilon_t$$

$$CSAD_t^{Down} = \alpha + \gamma_1 \left|R_{m,t}^{Down}\right| + \gamma_2 {R_{m,t}^{Down}}^2 + \varepsilon_t$$

Where, $\left|R_{m,t}^{Up}\right|$ and $\left|R_{m,t}^{Down}\right|$ are the absolute value of an equally weighted realized return of all available securities on day t when the market is up (down). ${R_{m,t}^{Up}}^2$ and $R_{m,t}^{Down^2}$ are the squared market value return. The presence of herding behavior to be detected by the statistically significant negative value of the coefficient γ_2. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Regression results from up market return			Regression results from down market return		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	1.74***	0.515***	**-0.067**	1.61***	0.504***	0.010***
	(25.98)	(11.4)	**(-3.6)*** **	(29.55)	(56.52)	(44.66)
Bearish Market	1.72***	0.577***	**-0.089**	1.65***	0.483***	0.011***
	(18.57)	(8.88)	**(-3.59)*** **	(20.31)	(52.23)	(45.50)
Bullish Market	1.66***	0.347***	0.085	1.55***	0.122	0.224
	(16.11)	(3.86)	(1.70)	(18.92)	(1.26)	(5.56)***
Crisis Market	1.63***	0.766***	**-0.132***	1.67***	0.598***	-0.014
	(3.65)	(3.36)	**(-1.83)**	(8.58)	(3.52)	(-0.35)
Extended Crisis Market	1.55***	0.605***	**-0.088****	1.49***	0.632***	0.008***
	(7.19)	(4.99)	**(-1.94)**	(13.53)	(28.52)	(12.98)
COVID-19 Market	2.502***	-0.208	0.836***	2.451***	0.120	-0.063
	(30.34)	(-0.87)	(4.88)	(12.13)	(0.43)	(-0.29)

Note: ***The coefficient is significant at 1% level. The t-statistics are reported in parentheses.

Table 6.14 reports the results estimated using equations 6.8 and 6.9 separately for up and down-market days using cross-sectional absolute deviation measures. In order to have herding behavior, the coefficient of γ_1 should be positively significant and the coefficient of γ_2 should have a statistically significant negative value. These conditions are confirmed for the overall market, and for bearish, crisis, & extended crisis periods in upward market movements revealing that investors tend to herd in these markets. While the sign of coefficient γ_2 has not been found negative in any of these markets in the downward market movements, revealing the absence of herding behavior.

Table 6.15: Regression results of CSSD measure in up and down market

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t^{Up} = \alpha + \gamma_1\left|R_{m,t}^{Up}\right| + \gamma_2 {R_{m,t}^{Up}}^2 + \varepsilon_t$$

$$CSSD_t^{Down} = \alpha + \gamma_1\left|R_{m,t}^{Down}\right| + \gamma_2 R_{m,t}^{Down^2} + \varepsilon_t$$

Where, $\left|R_{m,t}^{Up}\right|$ and $\left|R_{m,t}^{Down}\right|$ are the absolute value of an equally weighted realized return of all available securities on day t when the market is up (down). ${R_{m,t}^{Up}}^2$ and $R_{m,t}^{Down^2}$ are the squared market value return. The presence of herding behavior to be detected by the statistically significant negative value of the coefficient γ_2. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Regression results from up market return			Regression results from down market return		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	3.789***	-0.140	0.100	3.095***	1.171***	**-0.022*****
	(12.66)	(-0.23)	(0.27)	(11.58)	(10.60)	**(-4.97)**
Bearish Market	3.514***	-0.152	0.144	2.859***	1.167***	**-0.021*****
	(8.45)	(-0.16)	(0.41)	(10.92)	(11.78)	**(-5.2)**
Bullish Market	3.601***	0.011	0.237	3.146***	0.638	0.766***
	(8.59)	(0.01)	(0.40)	(5.40)	(0.74)	(20.3)
Crisis Market	3.845***	0.454	-0.022	3.253***	2.353	-0.402
	(3.51)	(0.29)	(-0.04)	(20.6)	(31.54)	(-1.01)
Extended Crisis	4.350***	-1.004	0.318	3.284***	1.365***	**-0.027*****
Market	(5.71)	(-1.09)	(0.81)	(3.48)	(6.08)	**(-2.8)**
COVID-19	5.774***	-1.932	1.787	5.773***	-3.888	2.371
Market	(5.91)	(-0.45)	(0.33)	(3.68)	(-0.75)	(0.36)

Note: ***The coefficient is significant at 1% level.
*The coefficient is significant at 10% level. The t-statistics are reported in parentheses.

Table 6.15 reports the results estimated using equations 6.8 and 6.9 separately for up and down-market days using cross-sectional standard deviation measures. The results suggest that herding behavior is not present in any of these market classifications during periods of up market. However, investors tend to herd during periods of falling market for the entire market, bearish, and extended crisis periods.

6.8.8 Examining asymmetric herding effect under different market states: high and low volume

Trading volume incorporates the quality and precision of the market information as well as information about price movements (Blume, Easley & O'hara, 1994). Behavioral theory states that when investors tend to imitate other investors' decisions by ignoring their own judgment, they make more trading on a particular stock. Trading volume, in aggregate, would be unusually high in the market. Our objective is to investigate whether trading volume can fuel herding tendency of investors in the equity market. Table 6.16 reports the results estimated using equations 6.10 and 6.11 separately for high and low trading volume states using cross-sectional absolute deviation measures.

Table 6.16: Regression results of CSAD measure in high and low volume state

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t^{V-High} = \alpha + \gamma_1^{V-High}\left|R_{m,t}^{V-High}\right| + \gamma_2^{V-High}\left(R_{m,t}^{V-High}\right)^2 + \varepsilon_t$$
$$CSAD_t^{V-Low} = \alpha + \gamma_1^{V-Low}\left|R_{m,t}^{V-Low}\right| + \gamma_2^{V-Low}\left(R_{m,t}^{V-Low}\right)^2 + \varepsilon_t$$

Where, $\left|R_{m,t}^{V-High}\right|$ $\left|R_{m,t}^{V-Low}\right|$ an equally weighted realized return of all available securities on day t when trading volume is high and low. $\left(R_{m,t}^{V-High}\right)^2$ $\left(R_{m,t}^{V-Low}\right)^2$ is the squared market return of this term. A statistically significant negative coefficients of γ_2 implies the presence of herding behavior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Regression results for high trading volume state			Regression results for low trading volume state		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	1.617***	0.561***	0.010***	1.744***	0.169***	0.052***
	(33.33)	(60.36)	(44.44)	(22.76)	(8.24)	(15.07)
Bearish Market	1.834***	0.135***	0.071***	1.647***	0.487***	0.011***
	(26.70)	(4.11)	(18.64)	(18.17)	(72.61)	(58.90)
Bullish Market	1.706***	0.080	0.349***	1.589***	0.275***	0.063
	(19.32)	(1.04)	(9.99)	(14.75)	(2.77)	(0.95)
Crisis Market	1.689***	0.399***	0.006	2.052***	0.422***	-0.032
	(9.95)	(3.87)	(0.16)	(5.39)	(2.85)	(-0.88)
Extended Crisis Market	1.515***	0.555***	0.015***	1.811***	0.322***	0.013***
	(14.13)	(19.77)	(13.11)	(10.29)	(9.44)	(16.83)
COVID-19 Market	2.359***	0.293***	0.771***	2.773***	0.376	0.100
	(18.10)	(1.78)	(3.72)	(9.37)	(1.10)	(0.38)

Note: ***The coefficient is significant at 1% level. The t-statistics are reported in parentheses.

Table 6.16 indicates that the coefficient of linear term is statistically significant for all the markers except the bullish period in high trading volume cases. The similar results we find for the low volume state confirming that rational asset pricing theory holds. The coefficient of non-linear term is also positively significant for most of the market conditions particularly in high and low trading volume states. This suggests that equity return dispersions increase rather than decrease evidencing the anti-herding behavior in Bangladesh equity market during periods of high and low trading volume. Our findings are against the assumption that cross-sectional dispersion should be negatively correlated with trading volume when investors tend to herd with the correlated market behavior. However, in our case, trading volume does not influence the tendency of herding behavior among investors in Bangladesh equity market. The positive correlation of trading volume and market return dispersion strongly evidences that high and low trading volume do not improve the herding tendency of market participants, which we can attribute to the low liquidity feature of Bangladesh equity market.

Table 6.17: Regression results of CSSD measure in high and low volume state

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t^{V-High} = \alpha + \gamma_1^{V-High}\left|R_{m,t}^{V-High}\right| + \gamma_2^{V-High}\left(R_{m,t}^{V-High}\right)^2 + \varepsilon_t$$

$$CSSD_t^{V-Low} = \alpha + \gamma_1^{V-Low}\left|R_{m,t}^{V-Low}\right| + \gamma_2^{V-Low}\left(R_{m,t}^{V-Low}\right)^2 + \varepsilon_t$$

Where, $\left|R_{m,t}^{V-High}\right|$ $\left|R_{m,t}^{V-Low}\right|$ an equally weighted realized return of all available securities on day t when trading volume is high and low. $\left(R_{m,t}^{V-High}\right)^2$ $\left(R_{m,t}^{V-Low}\right)^2$ is the squared market return of this term. A statistically significant negative coefficients of γ_2 implies the presence of herding behavior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Regression results for high trading volume state			Regression results for low trading volume state		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	3.005***	1.192***	**-0.021*****	3.454***	0.132*	0.150
	(11.0)	(10.61)	**(-4.86)**	(13.5)	(1.57)	(1.26)
Bearish Market	3.611***	-0.201*	0.123***	2.848***	0.975***	**-0.016*****
	(8.08)	(-1.58)	(2.76)	(11.2)	(14.7)	**(7.79)**
Bullish Market	3.684***	-1.533***	2.330***	3.448***	0.575	-0.381
	(8.36)	(-2.37)	(8.03)	(6.33)	(0.38)	(-0.20)
Crisis Market	4.086***	-0.349	0.173	3.426**	2.461**	-0.558
	(4.36)	(-0.26)	(0.23)	(2.07)	(1.98)	(-1.61)
Extended Crisis Market	3.661***	1.153***	-0.014	3.280***	0.987***	-0.016
	(3.00)	(2.89)	(-0.37)	(4.87)	(3.17)	(-0.55)
COVID-19 Market	4.240***	-0.580	1.660	6.733***	-1.499	1.187
	(6.98)	(-0.29)	(1.24)	(3.15)	(-0.28)	(0.17)

Note: ***The coefficient is significant at 1% level.
**The coefficient is significant at 5% level.
*The coefficient is significant at 10% level. The t-statistics are reported in parentheses.

The above table reports the herding regression results of CSSD measure under periods of high and low trading volume. The coefficient of $\gamma_1$is statistically significant and positive in most of the market scenarios for both high and low volume cases which is similar to the results presented for CSAD estimation. In high volume state, the coefficient γ_2 for the entire market is negative and statistically significant, indicating herding in this market. In low volume state, the coefficient γ_2 is negative and significant only for bearish market. There is clear evidence of herd behavior in Bangladesh equity market during periods of high and low volume when we estimate CSSD, but no herding is found in CSAD measure.

6.8.9 Herding Behavior during Extreme Trading Volume

We also examine whether investors tend to herd under the extreme trading volume conditions by using the magnitude of market return at its tail distributions in a non-linear fashion specified in equation 6.17**.**

Table 6.18: Regression results of CSAD and CSSD under extreme trading volume using the modified dummy variable model at 5% criterion

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{V-Abn\ High} R_{m,t}^2 + \gamma_4 D^{V-Abn\ Low} R_{m,t}^2 + \varepsilon_t$$

$$CSSD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{V-Abn\ High} R_{m,t}^2 + \gamma_4 D^{V-Abn\ Low} R_{m,t}^2 + \varepsilon_t$$

Where, $D^{V-Abn\ High}$ is the dummy variable takes a value 1 if market trading volume on day t lies in the extreme upper tail of the trading volume distributions; and zero otherwise. $D^{V-Abn\ Low}$ is the dummy variable that takes a value 1 if market trading volume on day t lies in the extreme lower tail of the trading volume distributions; and zero otherwise. $\left|R_{m,t}\right|$ is the absolute value of an equally weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. The 5% criterion is used as the percentage of the observations in the upper and lower tail of the distribution to define the extreme market conditions. In order to detect herding behavior, the coefficients γ_3 and γ_4 should be negatively significant. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
CSAD					CSSD			
Overall Market	0.386***	0.013***	**-0.140*****	-0.001	0.888***	-0.016***	0.611***	0.175
	(0.000)	(0.000)	**(0.000)**	(0.978)	(0.000)	(0.000)	(0.006)	(0.726)
Bearish Market	0.364***	0.013***	**-0.204****	-0.065	0.911***	-0.016***	0.007	-0.510
	(0.000)	(0.000)	**(0.026)**	(0.212)	(0.000)	(0.000)	(0.991)	(0.471)
Bullish Market	0.183***	0.187***	0.177***	-0.043	-0.510	0.941***	0.376	0.901
	(0.000)	(0.000)	(0.001)	(0.416)	(0.357)	(0.000)	(0.270)	(0.187)
Crisis Market	0.504***	-0.043	-0.004	-0.632	1.49	-0.141	1.92***	-2.08
	(0.000)	(0.126)	(0.968)	(0.289)	(0.128)	(0.595)	(0.005)	(0.982)
Extended Crisis Market	0.459***	0.011***	-0.136	0.157	1.07***	-0.019***	1.19***	-0.383
	(0.000)	(0.000)	(0.198)	(0.598)	(0.000)	(0.001)	(0.006)	(0.945)
COVID-19 Market	0.097	0.128	0.895**	0.270***	-2.57	1.84	4.95	2.84***
	(0.637)	(0.346)	(0.050)	(0.007)	(0.389)	(0.569)	(0.297)	(0.000)

Note: ***The coefficient is significant at 1% level.
**The coefficient is significant at 5% level. The p-values are reported in parentheses

The results disclose that the coefficient $\gamma_3$is statistically significant and negative for the entire market, and bearish markets under CSAD model at 5% tail distribution of trading volume. It confirms that investors in Bangladesh equity market avoid their own private analysis and tend to follow the aggregate market behavior during abnormal high trading volume, which suggest that fear and panic influence investors to replicate the others' decision when market experiences an extreme positive change in trading volume. Therefore, we conclude that herding behavior is present in entire market, and bearish period under the extremely higher trading volume, but not found under the extremely lower trading volume in any of these market period considered in this study.

6.8.10 Examining Asymmetric Herding Effect under different Market States: High and Low Volatility

Herding behavior may be influenced by the market volatility conditions. It is hypothesized that imitating tendency of investors would be more present during high volatility periods as opposed to the low volatility market days. Investors would find themselves more comfortable to suppress their prior beliefs in favor of market consensus during periods of high volatility and oscillation (Gleason, Mathur, & Peterson, 2004; Tan et al., 2008; Chiang & Zheng, 2010; Ferreruela & Mallor, 2021; Bharti & Kumar, 2022).

Table 6.19: Regression results of CSAD measure in high and low volatility market

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t^{Vol-High} = \alpha + \gamma_1^{Vol-High}\left|R_{m,t}^{Vol-High}\right| + \gamma_2^{vol-High}\left(R_{m,t}^{vol-High}\right)^2 + \varepsilon_t$$

$$CSAD_t^{vol-Low} = \alpha + \gamma_1^{Vol-Low}\left|R_{m,t}^{Vol-Low}\right| + \gamma_2^{Vol-Low}\left(R_{m,t}^{Vol-Low}\right)^2 + \varepsilon_t$$

Where, $\left|R_{m,t}^{Vol-High}\right|$ $\left|R_{m,t}^{Vol-Low}\right|$ is an equally weighted realized return of all available securities on day t when market volatility is high and low. $\left(R_{m,t}^{vol-High}\right)^2$ $\left(R_{m,t}^{Vol-Low}\right)^2$ are the squared market return of this term. A statistically significant negative coefficients of γ_2 implies the presence of herding behavior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Estimation for high volatility state			Estimation for low volatility state		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall	1.553***	0.611***	0.008***	1.792***	0.065***	0.067***
Market	(25.61)	(52.55)	(28.89)	(32.75)	(2.05)	(10.90)
Bearish	1.545***	0.601***	0.009***	1.807***	0.097***	0.065***
Market	(19.37)	(45.84)	(27.05)	(21.10)	(2.38)	(13.56)
Bullish	1.483***	0.393***	0.219***	1.692***	-0.079	0.491*
Market	(10.48)	(2.26)	(3.53)	(18.69)	(-0.39)	(1.81)

Crisis Market	1.892***	0.504***	**-0.053****	1.811***	0.271*	0.099
	(6.92)	(4.64)	**(-1.89)**	(8.37)	(1.77)	(0.04)
Extended Crisis Market	1.080***	0.853***	0.003***	1.799***	0.041*	0.071***
	(9.35)	(21.30)	(2.48)	(12.02)	(1.65)	(2.96)
COVID-19 Market	2.519***	0.132*	0.214	2.398***	0.201	0.703
	(9.41)	(1.69)	(1.07)	(27.13)	(0.33)	(0.59)

Note: ***The coefficient is significant at 1% level. **The coefficient is significant at 5% level. *The coefficient is significant at 10% level. The t-statistics are reported in parentheses.

Table 6.19 reports the asymmetric volatility herding regression results estimated from CSAD measure. The coefficient of linear components is positive and statistically significant for all market periods in high volatility phase. It is also significant for all periods except the bullish and COVID-19 periods in low volatility case and results are consistent with the predictions of rational asset pricing. The coefficient of non-linear components is negative and significant only for crisis period during periods of high volatility. The non-linear coefficient is positively significant for all the markets except the COVID-19 period under conditions of high and low market volatility implying anti-herding behavior in these market periods.

Table 6.20: Regression results of CSSD measure in high and low volatility market

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSSD_t^{Vol-High} = \alpha + \gamma_1^{Vol-High}\left|R_{m,t}^{Vol-High}\right| + \gamma_2^{vol-High}\left(R_{m,t}^{vol-High}\right)^2 + \varepsilon_t$$

$$CSSD_t^{vol-Low} = \alpha + \gamma_1^{Vol-Low}\left|R_{m,t}^{Vol-Low}\right| + \gamma_2^{Vol-Low}\left(R_{m,t}^{Vol-Low}\right)^2 + \varepsilon_t$$

Where, $\left|R_{m,t}^{Vol-High}\right|$ $\left|R_{m,t}^{Vol-Low}\right|$ is an equally weighted realized return of all available securities on day t when market volatility is high and low. $\left(R_{m,t}^{vol-High}\right)^2$ and $\left(R_{m,t}^{Vol-Low}\right)^2$ are the squared market return of this term. A statistically significant negative coefficients of γ_2 implies the presence of herding behavior. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (January 2010 –December 2011), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	Estimation for high volatility state			Estimation for low volatility state		
	α	γ_1	γ_2	α	γ_1	γ_2
Overall Market	2.746***	1.290***	**-0.024*****	3.777***	0.547	0.229
	(8.38)	(10.00)	**(-4.18)**	(14.32)	(-1.80)**	(0.64)
Bearish Market	2.414***	1.163***	**-0.019*****	3.524***	0.411*	0.215
	(8.41)	(13.08)	**(-6.16)**	(11.47)	(-1.77)	(0.82)
Bullish Market	3.161***	-0.481	1.512***	3.889***	3.048**	4.929**
	(3.75)	(-0.315)	(2.64)	(8.92)	(-1.86)	(1.84)
Crisis Market	3.100***	1.980***	-0.345	3.873***	8.425	-16.87
	(2.65)	(1.83)	(-1.29)	(2.21)	(0.57)	(-0.71)

Extended Crisis Market	2.896***	1.347***	**-0.025*** **	4.390***	-0.901**	0.267***
	(4.01)	(3.88)	**(-2.59)**	(11.26)	(-1.92)	(3.24)
COVID-19 Market	3.790	2.935	-0.883	6.009	-5.613	8.410
	(1.30)	(0.37)	(-0.18)	(7.38)*	(-0.86)	(0.67)

Note: ***The coefficient is significant at 1% level.
**The coefficient is significant at 5% level.
*The coefficient is significant at 10% level. The t-statistics are reported in parentheses.

The above table reports the asymmetric volatility herding regression results estimated from CSSD measure. There is clear evidence of herding behavior for the entire market, bearish, and extended crisis periods under conditions of high market volatility but no herding is present in low market volatility state. Results confirm that herding tendency of investors present in Bangladesh equity market during high volatility periods when CSSD model is estimated.

6.8.11 Herding Behavior during Extreme Market Volatility

We further investigate whether investors tend to exhibit herding behavior under the extreme market volatility conditions by using the magnitude of market return at its tail distributions in a non-linear fashion specified in equation 6.18**.**

Table 6.21: Regression results of CSAD and CSSD under the extreme market volatility using the modified dummy variables model at 5% criterion

The table reports the estimated parameters using the following regressions with AR(1) models:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{Vol-Abn\,High} R_{m,t}^2 + \gamma_4 D^{Vol-Abn\,Low} R_{m,t}^2 + \varepsilon_t$$

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{Vol-Abn\,High} R_{m,t}^2 + \gamma_4 D^{Vol-Abn\,Low} R_{m,t}^2 + \varepsilon_t$$

Where, $D^{Vol-Abn\,High}$ is the dummy variable that takes a value 1 if market volatility on day t lies in the extreme upper tail of the volatility distributions; and zero otherwise. $D^{Vol-Abn\,Low}$ is the dummy variable that takes a value 1 if market volatility on day t lies in the extreme lower tail of the volatility distributions; and zero otherwise. $|R_{m,t}|$ is the absolute value of an equally weighted realized retrun of all available securities on day t included in the market portfolio, $R_{m,t}^2$ is the market return square. The 5% criterion is used as the percentage of the observations in the upper and lower tail of the distribution to define the extreme market conditions. In order to detect herding behavior, the coefficients γ_3 and γ_4 should be negatively significant. The estimation is carried out for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory. Dow Theory identifies the bull market when each successive trend surpasses the previous one, and each reaction creates a higher level than the preceding one. In contrast, a bear market is depicted when each intermediate reaction rally stops at a lower level than the preceding one, while each uptrend rally reaches successively lower levels.

	CSAD				CSSD			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Overall	0.418***	0.012***	**-0.066*** **	0.064***	0.947***	-0.017***	-0.051	0.586***

Market	(0.000)	(0.000)	**(0.001)**	(0.000)	(0.000)	(0.000)	(0.848)	(0.000)
Bearish	0.413***	0.012***	**-0.104*****	0.058	0.987***	-0.018***	-0.031	0.585***
Market	(0.000)	(0.000)	**(0.000)**	(0.031)	(0.000)	(0.000)	(0.916)	(0.000)
Bullish	0.242***	0.172***	-0.043	0.054	0.276***	0.756***	-0.466	0.706***
Market	(0.000)	(0.000)	(0.384)	(0.100)	(0.000)	(0.000)	(0.339)	(0.000)
Crisis	0.562***	0.064*	-0.016	-0.015	1.56	-0.236	0.025	-0.207
Market	(0.003)	(0.098)	(0.915)	(0.940)	(0.381)	(0.551)	(0.982)	(0.961)
Extended	0.532***	0.010***	**-0.154*****	0.166	1.23***	-0.024***	-0.239	2.12***
Crisis Market	(0.000)	(0.000)	**(0.004)**	(0.10)	(0.000)	(0.000)	(0.593)	(0.000)
COVID-	0.078	0.384	-0.470***	0.027	-1.47	1.96	-1.65	0.232
19 Market	(0.720)	(0.036)	(0.004)	(0.649)	(0.745)	(0.744)	(0.808)	(0.752)

Note: ***The coefficient is significant at 1% level.
*The coefficient is significant at 10% level. The p-values are reported in parentheses

If the coefficient γ_3 and γ_4 are significantly negative, it would indicate the presence of herding behavior. The results delineate that herding behavior only prevails during abnormal high volatility state (as the coefficient γ_3 is negative and significant) for the entire, bearish, and extended crisis markets at its 5% tail distribution under CSAD model. It reinforces that investors in Bangladesh equity market avoid their own private analysis and tend to pursue the aggregate market behavior, which suggest that investors may find it easier to replicate the others' decision when market experiences an extreme positive volatility change. We conclude that investors in the Bangladeshi equity market do not herd under the extremely lower market volatility conditions.

6.8.12 Examination of Herding Behavior using Quantile Regression

Quantile regression (QR) has been considered a more robust technique over ordinary least squares (OLS) when the data set represents non-linear relationships. We intend to apply this technique in our research assuming that it can adequately capture the non-linear relationship between individual equity return dispersion and market return. Barnes & Hughes (2002) argue that quantile regression is a more robust method to examine the equity return dispersion in the distribution tails. The OLS estimates parameters based on the mean as a measure of location neglecting information regarding the tail of the distribution (Chiang et al., 2010). To overcome these problems, we employ quantile regression as a more efficient estimation method to investigate the response of return dispersion to the aggregate market movements.

A large number of empirical research conducted to examine the herding behavior across global equity market have been documented from the existing literature (Chiang et al., 2010; Chaffai & Medhioub, 2018; Choi & Yoon, 2020; Loang & Ahmad, 2022; Mishra, & Mishra, 2023; Pochea et al., 2021; Metawa et al,.2024; Ampofo et al,. 2023; Nguyen et al., 2024).

This research is the first one to examine investors' herding behavior in the Bangladesh equity market using the quantile regression approach.

Table 6.22: Quantile regression results of non-linear cross-sectional standard deviation and cross-sectional absolute deviation models

	CSAD				CSSD			
	Quantile Level	α	γ_1	γ_2	Quantile Level	α	γ_1	γ_2
Overall Market	0.25	0.309***	0.174***	0.008***	0.25	1.93***	0.529***	-0.005***
		(28.22)	(18.39)	(26.49)		(100)	(24.12)	(-6.42)
	0.50	0.221***	0.197***	0.005***	0.50	1.002***	0.295***	-0.006***
		(24.10)	(24.74)	(20.05)		(64.29)	(16.70)	(-10.29)
	0.75	0.212***	0.204***	0.018***	0.75	0.294***	0.157***	-0.005***
		(16.23)	(18.33)	(49.20)		(14.70)	(6.87)	(6.49)
Bearish Market	0.25	0.361***	0.207***	0.008***	0.25	1.944***	0.559***	-0.005***
		(31.45)	(21.58)	(27.49)		(80.03)	(24.70)	(-7.38)
	0.50	1.164***	0.452***	0.009***	0.50	0.848***	0.275***	-0.007***
		(39.09)	(19.33)	(24.23)		(50.74)	(17.70)	(-13.47)
	0.75	0.234***	0.213***	0.018***	0.75	0.280***	0.394***	-0.005***
		(15.89)	(17.27)	(47.26)		(8.70)	(13.12)	(-4.79)
Bullish Market	0.25	0.318***	0.039	0.114***	0.25	1.82***	0.677***	0.185***
		(13.63)	(0.87)	(4.36)		(42.45)	(5.24)	(-2.42)
	0.50	0.227***	0.050	0.132***	0.50	1.20***	0.248***	0.032
		(9.32)	(1.09)	(4.18)		(37.29)	(2.66)	(0.55)
	0.75	0.246***	-.062	0.241***	0.75	0.617***	-0.301***	0.302***
		(8.18)	(-1.09)	(7.12)		(13.28)	(-2.18)	(3.63)
Crisis Market	0.25	0.387***	0.682***	-0.050***	0.25	2.48***	1.41***	0.195
		(7.60)	(11.68)	(-3.67)		(7.76)	(3.31)	(-1.60)
	0.50	0.452***	0.546***	-0.031**	0.50	2.97***	-0.137	0.343***
		(8.01)	(9.60)	(-1.98)		(16.90)	(-1.00)	(5.25)
	0.75	0.354***	0.584	-0.045***	0.75	1.24***	-0.103***	0.179***
		(5.22)	(0.86)	(-2.22)		(6.23)	(-.390)	(2.42)
Extended Crisis Market	0.25	0.555***	0.441***	0.006***	0.25	2.21***	0.396***	-0.008***
		(22.55)	(26.24)	(12.98)		(35.82)	(10.24)	(-3.56)
	0.50	0.398***	0.428***	0.003***	0.50	2.14***	0.554***	-0.007***
		(19.13)	(28.96)	(8.84)		(32.86)	(13.54)	(-5.52)
	0.75	0.390***	0.392***	0.013***	0.75	0.735***	0.335***	-0.002***
		(10.85)	(15.13)	(18.14)		(7.05)	(5.15)	(-4.16)
COVID-19 Market	0.25	0.836***	0.223	0.243***	0.25	2.47***	0.281	0.832***
		(11.92)	(1.72)	(2.28)		(25.60)	(0.73)	(2.73)
	0.50	0.551***	0.235	0.164	0.50	1.187***	-0.606	1.29***
		(6.77)	(1.55)	(1.33)		(16.88)*	(1.44)	(3.91)
	0.75	0.368	0.238	-0.060	0.75	0.610***	-0.016	-0.012
		(5.00)	(1.74)	(-0.54)		(4.19)	(-0.19)	(-0.024)

Note: ***The coefficient is significant at 1% level.
*The coefficient is significant at 10% level. The p-values are reported in parentheses

The quantile regression approach describes the relationship between equity return dispersion and market returns under different quantile levels and provides a more convincing measurement of herding behavior. The quantile regression results using equation 6.29 are shown in above Table

6.22. It is observed that herding behavior is only detected for crisis period in CSAD model under each quantile level. Whereas, we find the evidence of herding in entire market, bearish, and extended crisis periods in case of CSSD model. Both results are similar to the findings we found when CSAD and CSSD models are estimated to use ordinary least squares (OLS).

6.8.12.1 Asymmetric Effect of Herding Behavior under different Market Conditions: Up and Down Markets

This part provides the quantile regression results estimated using equations 6.30 and 6.31 separately for cross-sectional absolute deviation and cross-sectional standard deviation measures under positive and negative market return conditions.

Table 6.23: Quantile egression Results of cross-sectional absolute deviation (CSAD) measure in up and down market

	Quantile regression results from positive market return				Quantile regression results from negative market return			
	Quantile Levels	α	γ_1	γ_2	Quantile Levels	α	γ_1	γ_2
Overall Market	0.25	0.241***	0.277***	**-0.034*** **	0.25	0.461***	0.233***	0.009***
		(9.23)	(8.05)	**(-2.57)**		(33.22)	(18.87)	(23.41)
	0.50	0.276***	0.286***	**-0.030*** **	0.50	o.299	0.217***	0.005***
		(8.38)	(6.60)	**(-2.61)**		(24.82)*	(20.25)	(17.35)
	0.75	0.274***	0.271***	**-0.025** **	0.75	0.368***	0.261***	0.015***
		(10.93)	(8.31)	**(-1.99)**		(13.04)	(10.38)	(19.81)
Bearish Market	0.25	0.366***	0.323***	**-0.029** **	0.25	0.535***	0.264***	0.009***
		(8.42)	(6.53)	**(-1.84)**		(30.04)	(17.58)	(20.27)
	0.50	0.350***	0.342***	**-0.042*** **	0.50	0.334***	0.240***	0.005***
		(9.65)	(8.28)	**(-3.01)**		(25.26)	(21.30)	(17.02)
	0.75	0.381***	0.296***	**-0.043*** **	0.75	0.223	0.230	0.017
		(9.05)	(6.16)	**(-2.71)**		(11.28)*	(13.63)*	(34.4)*
Bullish Market	0.25	0.341***	0.145***	0.070	0.25	0.416***	-0.063	0.187***
		(9.84)	(2.05)	(1.57)		(10.02)	(-0.88)	(4.70)
	0.50	0.236***	0.073	0.123***	0.50	0.371***	-0.041	0.218***
		(7.4)	(1.13)	(3.02)		(7.12)	(-0.45)	(4.36)
	0.75	0.239***	0.082	0.141***	0.75	0.374***	-0.344***	0.557***
		(4.47)	(0.75)	(2.06)		(7.60)	(-4.06)	(11.8)
Crisis Market	0.25	0.190	0.499***	-0.053	0.25	0.713***	0.653***	-0.039
		(1.81)	(4.28)	(1.54)		(5.80)	(5.23)	(-1.09)
	0.50	0.208	0.541**	**-0.073***	0.50	0.520***	0.489***	0.022
		(1.53)	(3.55)	**(-1.8)**		(3.70)	(3.45)	(0.55)
	0.75	0.309***	0.485***	**-0.053*** **	0.75	0.459***	0.460***	0.033
		(4.35)	(6.19)	**(-2.52)**		(2.72)	(2.68)	(0.68)
Extended Crisis Market	0.25	0.297***	0.467***	**-0.037** **	0.25	0.811***	0.609***	0.007***
		(5.92)	(8.05)	**(2.17)**		(17.9)	(21.1)	(8.80)
	0.50	0.290***	0.455***	**-0.050*** **	0.50	0.583***	0.589***	0.002***
		(4.34)	(5.95)	**(-2.20)**		(15.18)	(24.05)	(3.83)
	0.75	0.431***	0.404***	**-0.051*** **	0.75	0.558***	0.557***	0.009***

		(6.87)	(5.69)	**(-2.41)**		(10.14)	(15.87)	(9.1)
COVID-19 Market	0.25	1.17***	0.306***	0.250***	0.25	0.940***	-0.251***	0.619***
		(14.47)	(2.22)	(2.06)		(19.13)	(-2.09)	(6.6)
	0.50	0.929***	-0.042	0.448***	0.50	0.609***	-0.109	0.369***
		(7.56)	(-0.19)	(2.44)		(6.70)	(-0.48)	(2.11)
	0.75	0.693***	0.233	0.091	0.75	0.238***	0.105	0.050
		(5.62)	(1.11)	(0.49)		(2.51)	(0.44)	(0.27)

Note: ***The coefficient is significant at 1% level.
** The coefficient is significant at 5% level
*The coefficient is significant at 10% level. The p-values are reported in parentheses

The results of quantile regression clearly indicate that herding behavior is detected for the entire market, bearish, crisis, and extended crisis market periods in each of the quantile levels. No herding behavior is present in negative market returns condition for any of the market classifications. Findings from both positive and negative market returns conditions are similar to the OLS estimation presented in Table 6.14.

Table 6.24: Quantile egression Results of cross-sectional Standard deviation (CSSD) measure in up and down market

	Quantile regression results from positive market return				Quantile regression results from negative market return			
	Quantile Levels	α	γ_1	γ_2	Quantile Levels	α	γ_1	γ_2
Overall Market	0.25	2.072***	0.630***	-0.011	0.25	1.979***	0.504***	**-0.003*** **
		(56.90)	(7.74)	(-0.37)		(77.01)	(19.18)	**(-4.42)**
	0.50	1.28***	0.041***	0.022	0.50	1.31***	0.418***	**-0.007*** **
		(31.23)	(2.95)	(0.63)		(51.2)	(15.83)	**(-8.9)**
	0.75	0.512***	0.007	0.051	0.75	1.97***	0.882***	**-0.017*** **
		(13.36)	(0.08)	(1.51)		(30.02)	(13.15)	**(-7.60)**
Bearish Market	0.25	2.12***	0.765	-0.029	0.25	1.60***	0.572***	**-0.009*** **
		(53.28)	(9.53)***	(-1.08)		(51.9)	(21.53)	**(-11.34)**
	0.50	1.37***	0.280***	0.030	0.50	2.00***	0.522***	**-0.004*** **
		(23.1)	(2.30)	(0.76)		(70.8)	(21.30)	**(5.07)**
	0.75	0.792***	0.102	0.041	0.75	0.418***	0.444***	**-0.004*** **
		(21.1)*	(1.34)	(1.63)		(12.02)	(14.80)	**(-4.54)**
Bullish Market	0.25	1.85***	0.542***	-0.153	0.25	1.88***	0.454***	0.057
		(36.22)	(3.47)	(1.55)		(34.2)	(2.72)	(0.62)
	0.50	1.34***	0.224	0.095	0.50	1.281***	0.139	0.088
		(21.53)	(1.18)	(0.79)		(21.68)	(0.78)	(0.89)
	0.75	0.908***	0.597***	0.484***	0.75	0.664***	-0.920***	1.21***
		(10.65)	(-2.35)	(2.94)		(9.42)	(-4.33)	(10.32)
Crisis Market	0.25	2.72***	-0.142	0.145	0.25	2.69***	0.068	0.102
		(9.57)	(0.36)	(1.39)		(15.18)	(0.29)	(1.56)
	0.50	2.74***	0.072	0.096	0.50	3.15***	-0.329	0.379***
		(13.40)	(0.25)	(1.27)		(14.2)	(-1.18)	(4.6)
	0.75	1.37***	0.331	-0.023	0.75	1.34***	-0.268	0.278
		(7.26)	(1.25)	(-0.33)		(3.52)	(-0.55)	(2.01)

Extended Crisis Market	0.25	2.44***	-0.071	0.140***	0.25	2.26***	0.536***	**-0.004*****
		(25.46)	(-0.49)	(3.30)		(23.7)	(10.46)	**(-2.84)**
	0.50	2.72***	-0.136	0.160***	0.50	2.170***	0.908***	**-0.015*****
		(19.44)	(-0.64)	(2.57)		(18.13)	(14.11)	**(7.60)**
	0.75	1.62***	-0.357	0.142	0.75	0.564***	0.500	**-0.006*****
		(8.95)	(-1.30)	(1.77)		(4.45)	(7.32)	**(-3.06)**
COVID-19 Market	0.25	2.89***	0.574	0.407	0.25	2.74***	-0.741	1.56***
		(25.1)	(1.35)	(1.14)		(16.56)	(-0.92)	(2.57)
	0.50	3.04***	-1.14***	2.03***	0.50	1.90***	-0.901	1.08**
		(20.43)	(-2.15)	(4.57)		(11.39)	(-1.10)	(1.76)
	0.75	1.03***	-0.37	0.192	0.75	0.899***	-0.829	0.762
		(2.96)	(-0.29)	(0.17)		(4.07)	(-0.77)	(0.94)

Note: ***The coefficient is significant at 1% level.
** The coefficient is significant at 5% level
*The coefficient is significant at 10% level. The p-values are reported in parentheses

Table 6.24 reports the quantile regression results estimated using equations 6.30 and 6.31 separately for positive and negative market days for cross-sectional standard deviation measures. The results suggest that herding behavior is not present in any of these market classifications during periods of rising market. However, investors tend to herd during periods of falling market for the entire market, bearish, and extended crisis periods. This result is also supported by the results estimated under OLS.

6.8.12.2 Asymmetric Herding Effect under different Market conditions: high and low Volume

This part provides the quantile regression results estimated using equation 6.32 and 6.33 separately for cross-sectional absolute deviation and cross-sectional standard deviation measures under high and low trading volume conditions.

Table 6.25: Quantile regression results of cross-sectional absolute deviation (CSAD) measure in high and low volume state

	Quantile regression results for high trading volume state				Quantile regression results for low trading volume state			
	Quantile Levels	α	γ_1	γ_2	Quantile Levels	α	γ_1	γ_2
Overall Market	0.25	0.538***	0.294***	0.008***	0.25	0.352***	0.121***	0.039***
		(32.8)	(18.8)	(16.49)		(18.29)	(6.10)	(8.77)
	0.50	0.350***	0.269***	0.005***	0.50	0.220***	0.147***	0.053***
		(21.08)	(16.93)	(10.10)		(10.60)	(6.86)	(11.11)
	0.75	0.308***	0.313***	0.015***	0.75	0.280***	0.109***	0.061***
		(17.51)	(18.65)	(28.30)		(14.42)	(5.43)	(13.61)
Bearish Market	0.25	0.463***	0.154***	0.042***	0.25	0.439***	0.234***	0.008***
		(12.87)	(5.07)	(9.36)		(29.03)	(16.11)	(20.5)
	0.50	0.366***	0.153***	0.032***	0.50	0.275***	0.227***	0.005***
		(12.04)	(5.97)	(8.30)		(20.5)	(17.63)	(14.21)
	0.75	0.369***	0.133***	0.056***	0.75	0.285***	0.233***	0.026***
		(9.29)	(3.92)	(11.11)		(14.63)	(12.29)	(47.27)

Bullish Market	0.25	0.469***	0.041	0.174***	0.25	0.344***	0.060	0.119***
		(12.8)	(0.60)	(4.2)		(10.95)	(0.89)	(2.5)
	0.50	0.333***	-0.001	0.258***	0.50	0.230***	-0.029	0.168***
		(11.8)	(-0.03)	(8.13)		(6.90)	(-0.41)	(3.39)
	0.75	0.290***	-0.136	0.407***	0.75	0.254***	0.004	0.138**
		(5.40)	(-1.35)	(6.7)		(5.30)	(0.04)	(1.92)
Crisis Market	0.25	0.572***	0.550***	0.023	0.25	0.475***	0.474***	-0.023
		(3.54)	(3.46)	(-0.46)		(6.10)	(6.17)	(-1.1)
	0.50	0.461***	0.593***	-0.064	0.50	0.177	0.352***	0.001
		(2.51)	(3.29)	(-1.01)		(1.84)	(3.70)	(0.05)
	0.75	0.568***	0.427***	-0.009	0.75	0.202***	0.468***	-0.028
		(3.42)	(2.62)	(-0.17)		(2.4)	(5.67)	(-1.3)
Extended Crisis Market	0.25	1.10***	0.566***	0.016***	0.25	0.750***	0.458***	0.012***
		(33.8)	(23.34)	(15.51)		(24.46)	(19.5)	(18.1)
	0.50	0.911***	0.562***	0.013***	0.50	0.451***	0.391***	0.014***
		(20.2)	(16.80)	(9.32)		(14.9)	(15.4)	(20.9)
	0.75	0.744***	0.531***	0.011***	0.75	0.362***	0.392***	0.013***
		(14.36)	(13.8)	(6.85)		(8.82)	(11.73)	(14.8)
COVID-19 Market	0.25	1.65***	-0.04	0.940***	0.25	1.14***	-0.005	0.399***
		(9.37)	(-0.01)	(3.93)		(8.0)	(0.02)	(2.34)
	0.50	1.19***	0.132	0.354	0.50	0.04***	-0.020	0.388
		(7.8)	(0.48)	(1.17)		(4.30)	(-0.04)	(1.22)
	0.75	0.860***	-0.227	1.00***	0.75	0.408	0.743	-0.387
		(8.40)	(-1.2)	(7.29)		(1.20)	(1.23)	(-0.92)

Note: ***The coefficient is significant at 1% level.
** The coefficient is significant at 5% level
*The coefficient is significant at 10% level. The p-values are reported in parentheses

The quantile results from above Table 6.25 indicate that the coefficient of non-linear term is positively significant for most of the market periods in both high and low trading volume states. The herding coefficient is not statistically negative for each quantile level suggesting that equity return dispersions increase rather than decrease evidencing the anti-herding behavior in Bangladesh equity market during periods of high and low trading volume.

Table 6.26: Quantile regression results of cross-sectional standard deviation (CSSD) measure in high and low volume state

	Quantile regression results for high trading volume state				Quantile regression results for low trading volume state			
	Quantile Levels	α	γ_1	γ_2	Quantile Levels	α	γ_1	γ_2
Overall Market	0.25	2.07***	0.576***	-0.005***	0.25	1.90***	0.430***	0.047***
		(56.40)	(13.84)	(-4.82)		(86.40)	(12.6)	(15.97)
	0.50	1.54***	0.475***	-0.008***	0.50	1.42***	0.106***	0.161
		(46.92)	(12.74)	(-6.99)		(46.23)	(2.20)	(14.20)*
	0.75	0.306***	0.434	-0.006***	0.75	0.512***	-0.089	0.162***
		(7.84)	(9.80)***	(-4.32)		(14.12)	(-1.60)	(12.27)
Bearish	0.25	2.07***	0.589***	-0.037***	0.25	1.79***	0.561***	**-0.006*** **

Market		(51.10)	(9.40)	(-3.90)		(57.01)	(21.07)	**(-7.4)**
	0.50	1.71***	0.307***	0.032***	0.50	0.738***	0.301	**-0.008*****
		(42.32)	(4.88)	(3.45)		(23.4)	(1.28)	**(-9.6)**
	0.75	0.324***	-0.125***	0.162***	0.75	0.260***	0.219***	**0.020*****
		(8.91)	(-2.22)	(18.8)		(5.77)	(5.73)	**(17.17)**
Bullish Market	0.25	1.92***	0.642***	0.005	0.25	1.87***	0.565***	-0.097
		(28.90)	(3.27)	(0.04)		(14.12)	(3.64)	(-0.89)
	0.50	1.26***	0.123	0.293***	0.50	1.37***	0.279	-0.007
		(26.11)	(0.85)	(3.30)		(20.13)	(1.20)	(-0.04)
	0.75	1.09***	-2.60***	3.25***	0.75	0.839***	-0.129	0.104
		(13.35)	(10.67)	(22.2)		(9.5)	(-0.43)	(0.49)
Crisis Market	0.25	2.61***	0.147	0.068	0.25	2.11***	0.550***	-0.013
		(12.67)	(0.50)	(0.73)		(15.14)	(3.4)	(-0.30)
	0.50	2.84***	0.398	0.004	0.50	1.67***	0.021	0.102**
		(9.70)	(0.96)	(0.03)		(10.50)	(0.11)	(1.97)
	0.75	2.62***	-0.298	0.221	0.75	0.006	0.571	-0.098
		(9.0)	(-0.72)	(1.67)		(0.03)	(2.50)*	(-1.6)
Extended Crisis Market	0.25	2.53***	0.195***	0.024***	0.25	1.89***	0.476***	-0.001
		(26.9)	(2.85)	(8.26)		(10.1)	(4.30)	(-0.56)
	0.50	2.77***	0.248***	0.021***	0.50	2.55***	0.932***	-0.015***
		(32.47)	(3.97)	(7.84)		(19.7)	(11.3)	(6.47
	0.75	1.55***	0.304***	0.006	0.75	2.57***	0.902***	-0.021***
		(9.47)	(2.53)	(1.30)		(6.51)	(3.31)	(-2.50)
COVID-19 Market	0.25	2.93***	0.382	0.773***	0.25	2.71***	-2.27***	2.51***
		(20.41)	(0.98)	(2.59)		(17.32)	(-3.71)	(5.96)
	0.50	3.82***	-0.175***	3.17***	0.50	2.42***	-0.045	0.987
		(12.14)	(-2.05)	(4.87)		(6.23)	(0.03)	(0.92)
	0.75	3.43***	-2.23***	3.07***	0.75	1.17***	1.13	0.841
		(12.35)	(-2.92)	(5.34)		(3.21)	(0.90)	(-0.85)

Note: ***The coefficient is significant at 1% level.
** The coefficient is significant at 5% level
*The coefficient is significant at 10% level. The p-values are reported in parentheses

Quantile regression results from above Table 6.26 confirm that in high volume state, the coefficient γ_2 for the entire market is negative and statistically significant for each of the quantile level indicating the presence of herding in this market. In low volume state, the coefficient γ_2 is negative and significant only for bearish market at each quantile level representing the sign of herding in this market.

6.8.12.3 Asymmetric Herding Effect under different Market Conditions: High and Low Volatility

We also estimated quantile regression approach to measure whether the response of herding behavior among investors reflects any asymmetric patterns under conditions of high and low market volatility.

Table 6.27: Quantile regression results of cross-sectional standard deviation (CSAD) measure in high and low volatility market

	Quantile regression results for high volatility state				Quantile regression results for low volatility state			
	Quantile Levels	α	γ1	γ2	Quantile Levels	α	γ1	γ2
Overall Market	0.25	0.590***	0.292***	0.009***	0.25	0.274***	-0.003	0.076***
		(4.60)	(4.70)	(10.74)		(7.05)	(-0.10)	(17.8)
	0.50	0.351***	0.270***	0.005***	0.50	0.214***	0.062***	0.065***
		(3.86)	(7.04)	(6.94)		(7.58)	(1.90)	(17.5)
	0.75	0.250***	0.296***	0.015***	0.75	0.183***	0.100***	0.057***
		(2.49)	(4.79)	(7.12)		(4.44)	(2.59)	(12.59)
Bearish Market	0.25	1.76***	0.424***	0.008***	0.25	0.269***	-0.012	0.077***
		(3.90)	(4.21)	(8.41)		(7.35)	(-0.28)	(16.04)
	0.50	0.482***	0.347***	0.005***	0.50	0.246***	0.062	0.065***
		(2.31)	(4.11)	(3.99)		(6.74)	(1.67)	(15.6)
	0.75	0.312	0.307***	0.016***	0.75	0.203***	0.098***	0.058***
		(1.70)	(2.97)	(5.63)		(4.28)	(2.44)	(12.83)
Bullish Market	0.25	0.577***	-0.114	0.207	0.25	0.288***	0.257	-0.386
		(3.34)	(-0.22)	(0.55)		(6.46)	(1.50)	(-1.32)
	0.50	0.447***	-0.115	0.219***	0.50	0.223***	-0.165	0.509
		(5.22)	(-0.89)	(3.26)		(5.38)	(-1.05)	(2.07)
	0.75	0.462***	-0.522	0.471***	0.75	0.177***	-0.144	0.487
		(2.50)	(-1.69)	(2.64)		(3.22)	(-1.06)	(3.17)
Crisis Market	0.25	o.421***	0.615	**-0.051*** **	0.25	1.10***	0.034**	0.004
		(2.30)	(5.64)	**(-2.02)**		(9.54)	(1.8)	(-0.86)
	0.50	0.222***	0.383	-0.004	0.50	1.03***	0.021	0.005
		(2.17)	(2.73)	(-0.12)		(11.20)	(0.74)	(1.56)
	0.75	0.263***	0.327***	-0.027	0.75	1.41***	0.225***	0.001
		(1.63)	(2.12)	(0.46)		(7.65)	(3.50)	(-1.25)
Extended Crisis Market	0.25	0.813***	0.719***	0.006***	0.25	0.436***	0.269***	0.052***
		(7.27)	(9.61)	(3.38)		(3.62)	(3.51)	(7.17)
	0.50	0.808	0.827***	0.002	0.50	0.342***	0.181***	0.056***
		(1.77)	(5.48)	(0.85)		(3.91)	(2.91)	(8.36)
	0.75	0.632	0.888	0.000	0.75	0.416***	0.123	0.058***
		(0.93)	(1.71)	(0.07)		(5.56)	(1.51)	(6.64)
COVID-19 Market	0.25	0.733	0.338	0.110	0.25	1.02***	0.442	0.494
		(1.87)	(1.85)	(1.02)		(5.68)	(0.82)	(0.48)
	0.50	0.238	0.440***	0.070	0.50	0.945***	0.093	0.926
		(1.56)	(2.60)	(1.24)		(6.06)	(0.19)	(0.94)
	0.75	0.309	0.485***	0.004	0.75	0.646***	0.511	-0.540
		(1.30)	(2.06)	(0.04)		(2.16)	(0.90)	(-0.47)

Note: ***The coefficient is significant at 1% level.
*The coefficient is significant at 10% level. The p-values are reported in parentheses

Using the quantile regression approach to obtain the behavior of investors at different quantile levels, herding behavior is detected for crisis markets only at lower quantile in high volatility market conditions. The non-linear coefficient is positively significant for all the markets except the COVID-19 period under conditions of high and low market volatility implying anti-herding behavior in these market periods.

Table 6.28: Quantile regression results of cross-sectional standard deviation (CSSD) measure in high and low volatility market

	Quantile regression results for high volatility state				Quantile regression results for low volatility state			
	Quantile Levels	α	γ_1	γ_2	Quantile Levels	α	γ_1	γ_2
Overall Market	0.25	1.87***	0.669***	**-0.007*****	0.25	1.99***	0.524***	0.130***
		(37.77)	(10.60)	**(-4.83)**		(31.12)	(6.91)	(15.47)
	0.50	1.58***	0.728***	**-0.013*****	0.50	1.21***	0.114	0.155***
		(5.08)	(4.01)	**(-3.70)**		(3.77)	(0.99)	(16.70)
	0.75	0.284***	0.528***	-0.008	0.75	0.383***	0 .211***	0.172***
		(2.73)	(3.69)	(-1.69)		(9.83)	(-2.41)	(17.61)
Bearish Market	0.25	1.94***	0.700***	**-0.008*****	0.25	2.01***	0.442***	0.140
		(29.15)	(8.89)	**(-4.11)**		(27.33)	(5.47)	(15.70)*
	0.50	1.89***	0.892***	**-0.014*****	0.50	1.04***	0.043	0.161***
		(7.24)	(4.21)	**(-3.15)**		(2.48)	(0.26)	(12.8)
	0.75	1.26	0.938	-0.013	0.75	0.313***	-0.157	0.166***
		(1.67)	(2.73)*	(-1.58)		(7.98)	(-1.69)	(16.02)
Bullish Market	0.25	1.84***	0.637***	0.017	0.25	1.82***	1.04***	-0.328
		(12.44)	(2.19)	(0.13)		(32.61)	(2.52)	(-0.63)
	0.50	1.16***	0.615	0.008	0.50	1.36***	1.07***	-0.711
		(4.12)	(0.84)	(0.01)		(19.05)	(2.39)	(-1.13)
	0.75	1.81***	-1.77	1.70***	0.75	0.598	-0.684	0.936
		(3.15)	(-1.74)	(2.10)		(1.42)	(-1.42)	(2.09)
Crisis Market	0.25	2.13***	0.587	-0.026	0.25	1.54***	0.958***	0.002
		(7.64)	(1.94)	(-0.33)		(9.41)	(2.4)	(-0.41)
	0.50	1.89	0.170	0.114	0.50	1.30***	0.875	0.031
		(1.13)	(0.31)	(0.40)		(8.65)	(1.11)	(-0.65)
	0.75	0.417	-0.176	0.165	0.75	0.987***	1.01***	0.024
		(0.59)	(-0.36)	(0.79)		(7.68)	(2.47)	(-0.78)
Extended Crisis Market	0.25	1.71***	0.812***	**-0.010*****	0.25	2.43***	0.021	0.185***
		(5.66)	(3.94)	**(-2.07)**		(20.23)	(0.13)	(10.10)
	0.50	1.79***	1.21***	**-0.022*****	0.50	2.66***	-0.234	0.203***
		(3.43)	(3.20)	**(-2.29)**		(8.07)	(-1.43)	(10.69
	0.75	-0.555***	1.43***	**-0.041*****	0.75	1.31***	0.674***	0.225***
		(-2.14)	(9.77)	**(-11.5)**		(2.12)	(-4.10)	(12.85)
COVID-19 Market	0.25	2.49***	1.23	0.126	0.25	2.85***	0.556	1.96
		(4.07)	(0.78)	(0.23)		(13.10)	(0.29)	(0.47)
	0.50	1.43***	1.35***	0.170	0.50	2.19***	-0.977	3.30
		(3.11)	(2.10)	(0.86)		(7.22)	(-0.50)	(0.74)
	0.75	0.347	0.601	0.081	0.75	0.835***	-1.32	3.03
		(1.14)	(0.69)	(0.28)		(2.37)	(-0.39)	(0.42)

Note: ***The coefficient is significant at 1% level.
*The coefficient is significant at 10% level. The p-values are reported in parentheses

The quantile regression results from above Table 6.28 clearly evidences the presence of herding behavior for the entire market and bearish period at lower and median quantile. On the other hand, strong evidence of herding is present in extended crisis periods at each quantile level under conditions of high market volatility. Herding prevalence is not present at lower, median and upper quantiles for any of these markets in low market volatility state. All the results we estimated from quantile regression under both CSAD and CSSD models are consistent with estimations found in OLS method implying a more robust outcome about our models.

6.8.13 Structural Break Analysis

There are two equity market crises that have played a major role in the Bangladesh equity market during the study period. Both these crises' events are already reflected in the market state classification did for the research. Regardless of these, we also include some structural breaks tests to understand whether herding behavior can change before or after specific market events or policy changes in our equity market. The reform structural break analysis will help explain how regulatory authorities initiated various reforms strategies in the wake of the massive market crash experienced in the 2010-2011 period to reestablish investor confidence as well as stabilize the overall equity market. To measure the effect of these reforms on herding effects, we add a structural break at the post-market crash reform period. We implement short term, medium- and long-term reform windows to examine the behavior change, long and delayed, instigated by the change in policy. The COVID-19 structural break is an exogenous shock due to the unparalleled global pandemic that had a tremendous effect on investor behavior and equity market interactions. Both structural breaks will assist in testing the hypothesis of whether the tendencies of investor herding substantially modify during or following this disruption and these will give a stronger analysis of investor psychology.

Table 6.29: Regression results of CSAD under several structural breaks using dummy variable approach

This Table presents the estimated parameters of structural breaks using the following regressions with AR(1) model:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{COVID} + \gamma_4 D^{COVID} R_{m,t}^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{Reform} R_{m,t}^2 + \gamma_4 D^{Reform} R_{m,t}^2 + \varepsilon_t$$

Where D^{COVID} is the dummy variable that takes a value 1 during the COVID-19 period and zero otherwise; D^{Reform} is the dummy variable that takes a value 1 during regulatory reform periods and zero otherwise. $|R_{m,t}|$ is the absolute value of an equally weighted realized return of all accessible securities on day t included in the market portfolio, and $R_{m,t}^2$ is the market return square. The COVID period includes from 08/03/2020 to 31/12/2021. The short-reform period is from 01/04/2012 to 31/03/2013, the medium-reform window spans from 01/04/2012 to 31/03/2013, and the long-reform window is from 01/04/2012 to 31/12/2021.

	COVID-19 Structural Break	Short-Reform Structural Break	Medium-Reform Structural Break	Long-Reform Structural Break
α	1.599***	1.801	1.738***	1.682***
γ_1	0.402***	0.386	0.383***	0.406***
γ_2	0.0132***	0.014	0.013***	0.013***
γ_3	0.811***	-0.317	-0.183	0.054
γ_4	-0.105***	-0.031	-0.086	-0.088***
AR(1)	0.761***	0.789	-0.029***	0.813***
Adj. R-Square	0.892	0.889	0.888	0.889

Note: ***The coefficient is significant at 1% level.
CSAD is the cross-sectional absolute deviation. Both equations are estimated by HAC (Newey-West) method to account for heteroscedasticity and autocorrelation.
Source: Author's calculation using EViews software.

Findings from the different structural break analysis are reported in Table 6.29. The COVID-19 structural break reveals that strong presence of herding as evidenced by the negatively significant negative coefficient of γ_4. This implies that investors in the equity market tend to follow the aggregate market behavior, even in case of increased market volatility and heightened uncertainty. This behavioral shift among investors reflects the psychological convergence during the exogenous shocks caused by the global COVID-19 pandemic.

The short-reform structural break analysis indicates that the evidence of the shift in herding deviation has no statistically significant value since both the coefficient of the dummy variable and the coefficient of the interactive term is insignificant in a negative way. Nevertheless, the γ_2 coefficient is positive and significant, indicating that there was no herding during the pre-reform period. These results suggest that the regulatory changes that are introduced right after the market crash have no considerable effects on investors' imitation behavior in the short run. The outcomes of the medium-reform structural changes show that the general dispersion of equity returns has reduced, which means that the market has become more stable. Reforms reduced the noise and uncertainty in the market but did not affect collective behavior of investors in case of market movements as shown by statistically insignificant change in herding behavior. The long-term reform window has the indication of strong herding behavior because the coefficient γ_4 shows negativity and is significant. Although the general dispersion of equity returns did not vary substantially, investors were more collective when it came to moving in the market. It means that even with the continuing equity market volatility, regulatory reforms might respond slowly to affect investor psychology and long-run changes would slowly bring behavioral convergence.

6.8.14 Herding Behavior at the Industry Level

The bulk of empirical research on herding behavior in behavioral finance has predominantly concentrated on market-wide phenomena across the global equity markets. These include evidence from developed markets (Chang et al., 2000; Chiang & Zheng, 2010; Economou et al., 2015; Galariotis et al., 2016; Espinosa-Mendez & Arias, 2021; Pochea, 2021; Ampofo et al., 2023), emerging markets (Chiang et al., 2010; Prosad et al., 2012; Filip et al., 2015; Adem, 2020; Bharti & Kumar, 2022; Fang et al., 2021; Loang & Ahmad, 2022), frontier markets (Shah et al., 2017; Vo & Phan, 2019; Economou, 2020; Shrotryia & Kalra, 2022). A little attention has been paid to herding behavior at the sectoral level, particularly in both emerging and frontier equity markets. Herding behavior at the industry level may enable researchers to discern industry-specific patterns and market dynamics, which may remain undisclosed at the aggregate market level. In Bangladesh, Islam (2022) only investigated sectoral-level herding with focused on the single industry (banking sector). Highlighting the gap in the existing herding literature, this research will provide insights into industry herding tendencies of market participants to explore mispriced securities, exploit arbitrage opportunities, and manage the risk-return trade-offs in a more systematic manner.

Table 6.30: Descriptive statistics of the cross-sectional standard deviation (CSSD) of each industry for entire market

The cross-sectional standard deviation (CSSD) is calculated using the following equation:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} \frac{(R_{i,t} - R_{ind,t}}{N-1}}$$

The period studies for 14 industries in Bangladesh equity market are from January 2010 to December 2021. Mean and standard deviation are expressed in percent for CSSD of each industry.

	Mean	Median	Max.	Min.	SD	Skew	Kurt.	Jarque-Bera	Prob.
Bank	2.745	1.905	126	0.423	3.484	12.51	215	54311***	0.000
NB	3.175	2.569	58.60	0.726	4.236	10.28	120	16986***	0.000
Insurance	2.979	2.539	89.54	1.033	3.325	16.45	358	15107***	0.000
Textile	3.859	3.150	69.37	0.976	4.480	9.354	108	13622***	0.000
Pharmaceuticals	2.929	2.567	64.12	0.517	2.944	13.86	231	62638***	0.000
Engineering	3.172	2.647	61.97	0.443	3.507	11.45	167	32772***	0.000
Fuel & Power	2.624	2.158	77.83	0.486	3.765	13.11	205	49590***	0.000
Food	3.315	3.005	137	0.914	3.445	24.86	863	88097***	0.000
IT	2.997	2.424	186	0.081	2.501	24.47	643	48953***	0.000
Miscellaneous	2.762	2.488	24.80	0.353	1.526	3.387	34.23	12102***	0.000
Service	2.426	1.871	133	0.065	3.890	26.27	863	88130***	0.000
Tannery	2.480	1.961	132	0.0774	3.745	23.72	717	60674***	0.000
Cement	2.240	1.885	12.99	0.151	1.519	1.978	9.58	6993***	0.000
Ceramic	2.718	2.291	20.83	0.045	1.874	2.216	13.47	15334***	0.000

Note: *** The coefficient is significant at the 1% level.

Table 6.30 details the summary statistics of cross-sectional standard deviation (CSSD) of 14 industries listed on the Dhaka Stock Exchange (DSE). The cement industry has the lowest average of CSSD of 2.25% and lowest volatility of 1.52%. The textile industry has the highest average value of 3.86%, with highest variations of 4.8%. The CSSD ranges from a minimum of 0.045% in ceramic industry to a maximum of 137% in the food industry. The CSSD value shows a departure from normality as documented by significant value of Jarque-Bera test statistics.

6.8.14.1 Examining the non-linearity in the Cross-sectional standard deviation (CSSD)-Industry Return Nexus

This section begins with the analysis of basic non-linear specification of cross-sectional standard deviation (CSSD) measure to examine herding tendency among investors in Bangladeshi equity market at the industry level.

Table 6.31: Regression results of the non-linear cross-sectional standard deviation model

This table reports the estimated coefficients using the following regression with AR(1) model:

$$CSSD_{ind,t} = \alpha + \gamma_1 \left| R_{ind\_m,t} \right| + \gamma_2 R_{ind\_m,t}^2 + \varepsilon_t$$

Where, $\left| R_{ind\_m,t} \right|$ is the absolute value of an equally weighted realized return of all available securities on day t in a particular industry at time t. $R_{ind\_m,t}^2$ is the industry market return squared. The presence of negative and significant coefficient of γ_2 would be the indicative of herd behavior. The model is estimated for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), and COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory.

	Overall Market		Bearish Market		Bullish Market	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Banking	2.19***	0.121***	-.172***	1.70***	0.03***	2.94***
NBFI	-0.270***	0.301	-0.613***	0.313***	0.172***	0.283***
Insurance	-0.081***	0.363***	-0.502***	0.43***	0.26***	0.33***
Textile	1.49***	0.19***	1.14***	0.252***	1.79***	0.153***
Pharmaceuticals	0.732***	0.224***	-0.545***	0.446***	1.75***	0.142***
Engineering	0.793***	0.195***	0.133***	0.226***	1.67***	0.158***
Fuel & Power	1.42***	0.085***	-0.674***	0.376***	2.17***	0.047***
Food & Allied	1.12***	0.093***	0.095***	0.236***	1.29***	0.086***
IT	0.423***	0.037***	0.118***	0.039***	0.504***	0.046***
Miscellaneous	0.054***	0.137***	0.016	0.123***	-0.092	0.234***
Service	0.592***	0.018***	0.402***	**-0.015*** **	0.891***	0.016***
Tannery	1.07***	0.001***	0.471***	0.015***	1.07***	0.006***
Cement	0.541***	**-0.017*** **	0.611***	**-0.087*** **	0.283***	0.091***
Ceramic	0.341***	0.042***	0.612***	**-0.045*** **	0.213***	0.112***
	Crisis Market		Extended Crisis Market		COVID-19 Market	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
Banking	-1.52***	0.610***	2.17***	0.071***	0.493***	0.386***
NBFI	0.362***	**-1.38*** **	0.305***	**-0.783*** **	0.297**	0.415***
Insurance	0.252***	**-0.185** **	0.284***	**-0.257* **	0.931***	0.374***
Textile	0.271***	**-0.722*** **	0.263***	**-0.536*** **	1.65***	0.531***
Pharmaceuticals	0.173***	0.065	0.184***	0.361***	0.584***	0.401***
Engineering	-0.061***	0.490***	0.243***	**-0.362*** **	1.63***	0.541***
Fuel & Power	0.132***	**-0.491*** **	0.127***	**-0.324*** **	1.44***	0.236***

Food	-0.061	0.296	-0.035	0.153	1.78***	0.061***
IT	-0.062**	0.521***	-0.045**	0.451***	1.10***	0.032***
Miscellaneous	-0.024	0.291	-0.017	0.226*	-0.297	0.353***
Service	0.025***	0.005	0.026***	0.072	0.431***	0.804***
Tannery	0.006	0.123	0.017***	0.272***	0.781***	0.117***
Cement	-0.023	0.205	-0.064***	0.474***	0.396***	0.123***
Ceramic	-0.041	0.440**	-0.042***	0.371***	0.124	0.135***

Note: ***The coefficient is significant at the 1% level,
** The coefficient is significant at the 5% level.

Table 6.31 reports the regression results of herding behavior by examining the relationship between return dispersion and nonlinear market return for all market classifications. A statistically negative value of the coefficient of γ_2 is consistent with herding activity. The evidence shows that herding behavior is only present in cement industry during the entire market period. In bearish market, herding behavior is prevalent in three industries, namely service & real estate, cement, and ceramic. Investors in these industries display a higher level of risk aversion and market sentiment, following the industry trend. In crisis market, investors demonstrate a collective response to market uncertainty and tend to exhibit herding activities in non-banking financial institutions, insurance, textile, and fuel & power sectors. The extended crisis market displays the findings like the crisis market except that we find herding behavior in one more industry- engineering. The bullish and COVID-19 markets do not represent any evidence of industry-level herding in the Bangladeshi equity market, as none of the non-linear coefficient shows a statistically negative sign. Findings reveal that herding tendency of investors is more prevalent in crisis and extended crisis markets relative to the bearish and overall markets. This tends to confirm that panic or fear of losses, emotions driven herd mentality, negative news about the market may trigger investors in Bangladeshi equity market to follow the aggregate industry behavior in crisis period than the other market conditions.

6.8.14.2 Examining Asymmetric Effect of Industry Herding Behavior under different Market Conditions: Up and Down Markets

We investigate whether herding tendency of investors at the sectoral level represents the nonlinear relation between equity return dispersion and industry portfolio returns. The behavior of investors in equity market may represent asymmetric pattern depending on the different market conditions. To detect herding behavior in different market return conditions, the coefficients of up and down- market dummy variables should be significant and negative.

Table 6.32: Regression results of CSSD measure in up and down market

This table reports the estimated coefficients using the following regression with AR(1) model:

$$CSSD_{ind,t} = \alpha + \gamma_1 D\left|R_{ind\_m,t}\right| + \gamma_2(1-D)\left|R_{ind\_m,t}\right| + \gamma_3 D R_{ind\_m,t}^2 + \gamma_4(1-D)R_{ind\_m,t}^2 + \varepsilon_t$$

Where, D is the dummy variable that takes a value of 1 if market return on a particular day is positive; otherwise equal to zero. $\left|R_{ind\_m,t}\right|$ is the absolute value of an equally-weighted realized return of all available securities on day t in a particular industry at time, $R_{ind\_m,t}^2$ is the industry market return squared.

The presence of negative and significant coefficients of γ_3 and γ_4 would be the indicative of herd behavior. The model is estimated for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory.

	Overall Market				Bullish Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	2.18***	2.10***	0.110***	0.142***	0.029***	0.072***	0.967***	0.812***
NBFI	-0.27***	0.28***	0.305***	0.302***	0.324***	0.219***	0.095***	0.109***
Insurance	0.105***	0.360***	0.330***	0.470***	0.190***	0.143***	0.108***	0.107***
Textile	1.63***	1.30***	0.185***	0.206***	0.842***	0.734***	0.022***	0.043***
Pharma	0.071	0.551***	0.412***	0.196***	0.655***	0.774***	0.091***	0.043***
Engineering	0.773***	0.817***	0.201***	0.195***	0.784	0.873	0.045	0.043
Fuel & Power	1.48***	1.36***	0.077***	0.084***	1.12***	1.16***	0.013***	0.012***
Food	0.821***	1.02***	0.167***	0.090***	0.530***	0.595***	0.105***	0.038***
IT	0.734***	0.585***	0.010***	0.013***	0.570***	0.211***	0.019***	0.131***
Miscellaneous	0.389***	0.475***	0.063***	0.267***	0.342***	0.224***	0.070***	0.237***
Service	0.737***	0.387***	0.013***	0.019***	0.820***	0.541***	0.005***	0.010***
Tannery	0.871***	0.903***	0.028***	0.011***	0.674***	0.478***	0.019***	0.028***
Cement	0.745***	0.345***	**-0.044*****	0.015***	0.467***	0.010***	0.032***	0.158***
Ceramic	0.748***	0.059	-0.037***	0.130***	0.536***	0.083	0.007	0.136***
	Bearish Market				Crisis Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	0.185***	0.171***	1.71***	1.67***	1.61***	1.73***	0.679***	0.606***
NBFI	0.768***	0.633***	0.356***	0.302***	0.023	0.373***	-0.292	**-1.27*****
Insurance	0.469***	0.584***	0.061***	0.510	0.280***	0.427***	**-0.702***	-0.688
Textile	0.743***	0.906***	0.429***	0.244***	0.240***	0.330***	**-0.874*****	**-1.04*****
Pharma	0.436	0.172	0.451	0.102	0.260***	0.188	-0.201	-0.138
Engineering	0.061***	0.101**	0.255***	0.228***	0.065***	0.180***	0.376***	-0.223
Fuel & Power	0.711***	0.680***	0.368***	0.391***	0.135***	0.141	**-0.543*****	-0.476
Food	0.402***	0.802***	0.243***	0.519***	0.083	0.031	0.382*	0.124
IT	0.207***	0.011	0.028***	0.032***	0.061*	-0.071**	0.521**	0.544**
Miscellaneous	0.263***	0.291***	0.081***	0.187***	0.032	0.013	0.322	0.156
Service	0.449***	0.451***	0.008	**-0.032****	0.023**	-0.108	0.074	0.572*
Tannery	0.875***	0.412***	**-0.073****	0.016	0.061	-0.129	-0.023	0.587
Cement	0.658***	0.582***	**-0.091*****	**-0.072*****	0.001	-0.038	0.137	0.254
Ceramic	0.645***	0.474***	**-0.063*****	0.002	0.040*	-0.049	0.608**	0.305
	Extended Crisis Market				COVID-19 Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	2.05***	1.51***	0.058***	0.189***	0.001	0.486	1.26	0.538
NBFI	0.274***	0.304***	**-0.808*****	**-0.655*****	0.027**	0.333	0.412***	0.410***
Insurance	0.275***	0.549***	**-0.684*****	**-1.11*****	0.817***	0.911***	0.367***	0.404***
Textile	0.215***	0.299***	**-0.418*****	**-0.758*****	1.65***	1.69***	0.517***	0.550***
Pharma	0.522***	0.196***	**-0.954*****	-0.269	0.632***	0.475***	0.383***	0.427***
Engineering	0.241***	0.247***	**-0.404*****	**-0.305*****	1.62***	1.50***	0.624***	0.518***
Fuel & Power	0.121***	0.131***	**-0.239*****	**-0.438*****	0.962***	1.51***	0.331***	0.198***
Food	0.088**	0.107**	0.264*	-0.196	0.505***	1.46***	0.452***	0.073***
IT	0.051**	0.029	0.517***	-0.130	1.24***	0.915***	0.033***	0.037***
Miscellaneous	0.100***	-0.021	0.868***	0.186	0.208	0.753***	0.190***	0.464***

Service	0.021*	0.025***	0.053	-0.068	0.711***	-0.128	0.052**	0.183***
Tannery	0.107***	0.018**	0.837***	0.229***	1.12***	0.810***	0.064**	-0.019
Cement	0.077***	-0.054**	0.653***	0.314**	0.568***	0.128	0.052	0.233***
Ceramic	0.080***	0.064**	0.708***	0.207	0.520**	-0.282	0.042	0.216***

Note: ***The coefficient is significant at the 1% level,
** The coefficient is significant at the 5% level.
* The coefficient is significant at the 10% level.

Table 6.32 reports regression results of industry herding behavior during the up and down-market conditions. Herding behavior does not prevail at industry level for the entire market period except the cement industry, which shows the sign of herding during the up-market period. In bearish markets, two industries including tannery and ceramic exhibit herding behavior during the up market and service industry during the down-market period. However, the cement industry reveals herding during both up and down markets. In the case of market crisis, insurance and fuel & power industries exhibit herding activity during up market, and investors in the non-bank financial institutions tend to herd when market experiences a downturn. Textile industry tends to herd when market went up and down. The evidence reported suggests that more industries tend to manifest herding activities during both up and down markets in the extended crisis market period. These industries include non-bank financial institutions, insurance, textile, engineering, and fuel & power. Conversely, investors in the pharmaceuticals industry form herding behavior during downward price movements. As stated earlier, the magnitude of investors' herding behavior is significantly higher in crisis and extended crisis markets relative to other market classifications. The representation of these results affirms that market participants become more sensitive to the displeasure of loss and have a greater tendency to protect their losses by following industry market trends in these markets. We find no asymmetric industry herding behavior on the part of market participants in the Bangladeshi equity market in the bullish and COVID-19 market periods, which suggests a potential divergence in investor behavior relative to industry consensus during these periods.

6.8.14.3 Examining Asymmetric Effect of Industry Herding Behavior under different Market Conditions: High and Low Volatility Markets

High or low market volatility may represent an indication of the activities level of equity market participants in response to the unusual flow of information. Information asymmetry can influence herding behavior of market participants, which pushes equity prices to deviate away from the fundamental value, and can cause volatility in the markets (Bikhchandani, Hirshleifer, & Welch, 2005; Nofsinger & Sias, 1999). Hence, there should be a correlated behavior between herding activity and volatility in the equity markets.

Table 6.33: Regression results of CSSD measure in high and low volatility market

This table reports the estimated coefficients using the following regression with AR(1) model:

$$CSSD_{ind,t} = \alpha + \gamma_1 D^{Vol-High}\left|R_{ind\_m,t}\right| + \gamma_2\left(1 - D^{Vol-High}\right)\left|R_{ind\_m,t}\right| + \gamma_3 D^{Vol-High} R^2_{ind\_m,t} + \gamma_4\left(1 - D^{Vol-High}\right) R^2_{ind\_m,t} + \varepsilon_t$$

Where, $D^{Vol-High}$ is the dummy variable that takes a value of 1 if market volatility on a particular day is high; otherwise, equal to zero. The volatility of daily industry returns is perceived to be high (low) on day t if it is greater (lower) than the last 30 days moving averages. $|R_{ind\_m,t}|$ is the absolute value of an equally weighted realized return of all available securities on day t in a particular industry at time, $R^2_{ind\_m,t}$ is the industry market return squared. The presence of negative and significant coefficients of γ_3 and γ_4 would be the indicative of herd behavior. The model is estimated for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory.

	Overall Market				Bullish Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	2.46***	1.89***	0.090***	0.183***	0.014***	0.147***	1.07***	0.488**
NBFI	0.197***	0.331***	0.279***	0.323***	0.081***	0.300***	0.142***	0.262
Insurance	0.463***	0.206***	0.436***	0.296***	0.147**	1.00***	0.023***	0.540***
Textile	1.09***	1.41***	0.371***	0.188***	4.09***	1.43***	0.039	0.660***
Pharma	0.131***	0.530***	0.456***	0.189***	3.89***	0.446	0.348***	0.364***
Engineering	0.872***	0.777***	0.223***	0.188***	0.251***	0.662	0.391	0.691***
Fuel & Power	0.335***	0.843***	0.304***	0.089***	3.56***	0.801***	0.087***	0.073***
Food	0.862***	1.00***	0.194***	0.091***	2.72***	0.361***	0.847***	0.887***
IT	0.700***	0.274***	0.031***	0.030***	0.922***	0.033***	0.144***	0.239***
Miscellaneous	0.402***	0.001***	0.027***	0.163***	0.406***	0.106***	0.213***	0.717***
Service	0.615***	0.552***	0.026***	0.016***	1.38***	0.221***	0.241***	0.246***
Tannery	0.620***	0.582***	0.037***	0.013***	0.747***	0.238***	0.326***	0.284***
Cement	0.866***	0.469***	**-0.057*****	0.001	0.558***	0.677***	0.152***	0.341***
Ceramic	0.574***	0.291***	0.019**	0.055***	0.332***	0.681	0.159	0.082***
	Bearish Market				Crisis Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	0.168***	0.591***	1.85***	2.62***	1.80***	5.35***	0.656***	0.562***
NBFI	0.580***	0.082***	0.310***	0.156***	0.377***	0.362***	**-1.51*****	**-1.01****
Insurance	0.677***	-0.325	0.462***	0.523***	0.272***	0.477	-0.372	-0.351
Textile	1.36***	2.87***	**-0.235*****	**-0.774*****	0.266***	0.528***	**-0.492*****	1.68***
Pharma	0.105***	0.535***	0.242***	0.446***	0.175***	0.231	0.149	0.873
Engineering	0.148***	0.060***	0.211***	0.249***	0.068***	0.113	0.510***	0.635
Fuel & Power	0.687***	0.663***	0.387***	0.368***	0.133***	0.259	**-0.505*****	-0.128
Food	0.212***	1.12***	0.226***	0.-348	0.054	0.545	0.183	-0.499
IT	0.080***	0.267	0.031***	0.191***	0.073**	0.011	0.523**	0.180
Miscellaneous	0.001***	0.394***	0.132***	0.099	0.021	0.106	0.304	0.633
Service	0.291***	0.060***	0.020**	0.263***	0.025***	0.204	-0.073	-0.149
Tannery	0.467***	0.424**	0.015***	0.016	0.051	0.878	-0.198	-1.57
Cement	0.558***	0.536***	**-0.074*****	0.021***	0.006	-0.174	0.039	-0.142
Ceramic	0.470***	0.122	**-0.022****	0.303***	0.027*	0.395	0.009	-0.290
	Extended Crisis Market				COVID-19 Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	2.57***	4.78***	0.055***	**-1.16****	0.499***	0.120	0.383**	1.82***
NBFI	0.302***	0.090***	**-0.757*****	0.015	0.180**	0.316	0.421***	0.771**
Insurance	0.301***	0.457	**-0.384****	-0.358	1.30***	4.60***	0.352***	**-3.52****
Textile	0.253***	0.288**	**-0.312*****	1.01***	1.94***	3.20**	0.502***	-1.08
Pharma	0.182***	0.203	0.462***	0.155	0.437***	0.414	0.415***	1.26**
Engineering	0.250***	0.007	**-0.352*****	0.671***	1.45***	1.10	0.585***	1.20
Fuel& Power	0.127***	0.359*	**-0.361*****	-0.43	1.66***	2.81**	0.214***	-1.11

Food	0.007**	0.493	0.029	-0.457	1.62***	0.960**	0.069***	0.521***
IT	0.054**	0.115	0.450***	-0.058	1.09***	1.12**	0.035***	0.059
Miscellaneous	0.011***	-0.035	0.188	0.367	0.540***	1.57**	0.401***	1.61***
Service	0.023*	0.199	-0.037	-0.123	0.319***	-0.311	0.095**	0.575***
Tannery	0.018***	0.046	0.249***	0.241	0.750***	0.766***	0.123**	0.192
Cement	0.050***	-0.105**	0.398***	0.089	0.359***	0.640	0.134***	0.137
Ceramic	-0.014	0.208	0.201	0.018	0.191***	0.694	0.117***	-0.074

Note: ***The coefficient is significant at the 1% level.
** The coefficient is significant at the 5% level.
* The coefficient is significant at the 10% level.

Table 6.33 reports the herding behavior of investors at industry level during periods of high and low volatility in the Bangladeshi equity market using the cross-sectional standard deviation (CSSD) measure. The results show that all industries except cement do not exhibit herding behavior during periods of high and low market volatility for the entire market. Investors in the cement industry are more likely to follow industry trends when the market is driven by high volatility. Herding behavior is more pronounced for cement and ceramic industries during periods of high volatility, and for the textile industry during periods of both high and low volatility in the bearish market. In the crisis market, herding behavior is more apparent for the textile and fuel & power industries during periods of high market volatility, as supported by negatively significant coefficient of γ_3. Investors in non-bank financial institutions reveal evidence of herding not only during periods of high volatility but also during periods of low market volatility. Herding behavior is strongly present across five industries, including non-bank financial institutions, insurance, textile, engineering, and fuel & power during high volatility period in extended crisis market. Whereas banking industry exhibits herding during periods of low market volatility. We could also observe that market participants exert the strongest degree of herding in crisis and extended crisis markets compared to the other markets, since their coefficients are significantly higher. No herding phenomenon is detected from any industry in the bullish and COVID-19 markets. This suggests that market participants in the Bangladeshi equity market, in general, do not adhere to overall market consensus in response to high or low market volatility. Instead, they rely more on their independent beliefs and information while making investment decisions.

6.8.14.4 Industry Herding Behavior under Extreme Market Conditions

Empirical studies on herding activity document that market participants are more likely to abandon their private beliefs and gear more towards aggregate market behavior particularly when market experiences extreme or high turbulence (Change et al., 2000; Lao & Singh, 2011; Bhaduri & Mahaparta, 2013; Bernales et al., 2020; Vo & Phan, 2016; Arjoon & Bhatnagar, 2017; Bouri et al., 2021; Indars et al., 2019). Table 6.34 reports on the industry herding effect during the extreme market conditions by using the magnitude of market return at its tail distributions in a non-linear fashion specified in modified equation 6.5. We specify the extreme up (down) market as 1% criterion of the upper and lower tail of the market return distributions.

Table 6.34: Regression results of CSSD under extreme market movements using the modified dummy variable model at 1% criterion

Note: This table reports the estimated coefficients using the following regression with AR(1) model:

$$CSSD_{ind,t} = \alpha + \gamma_1 D_t^U \left|R_{ind\_m,t}\right| + \gamma_2 D_t^D \left|R_{ind\_m,t}\right| + \gamma_3 D_t^U R_{ind\_m,t}^2 + \gamma_4 D_t^D R_{ind\_m,t}^2 + \varepsilon_t$$

Where, D_t^U takes a value of 1 if the industry return on day t lies in the extreme upper tail of the distributions; and zero otherwise, and D_t^D takes a value of 0 if the returns of the industry on day t lies in the extreme lower tail of the distributions; and zero otherwise. The 1% criterion represents the percentage of of observations in the upper and lower tail of the industry return distributions. $\left|R_{ind\_m,t}\right|$ is the absolute value of an equally weighted realized return of all available securities on day t in a particular industry at time, $R_{ind\_m,t}^2$ is the industry market return squared. The presence of negative and significant coefficients of γ_3 and γ_4 would be the indicative of herd behavior. The model is estimated for the overall market (January 2010-December 2021), bearish, bullish, crisis (July 2010- June 2011), extended crisis (September 2009-April 2012), COVID-19 markets (March 08-December 2021). Bullish and bearish markets are determined applying the Dow Theory.

	Overall Market				Bullish Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	1.90***	2.02***	0.122***	0.143***	0.042***	0.079***	2.40***	0.3.03**
NBFI	0.553***	0.239***	0.328***	0.299***	0.038***	0.439***	0.289***	0.270***
Insurance	0.398***	0.327***	0.353***	0.465***	0.052	0.548***	0.336***	0.396***
Textile	1.34***	1.31***	0.202***	0.200***	1.39***	2.12***	0.165	0.143***
Pharma	0.506***	0.672***	0.474***	0.186***	0.021	2.62***	0.437***	0.067***
Engineering	0.421***	0.943***	0.225***	0.183***	1.25***	2.61***	0.172***	0.090***
Fuel & Power	1.21***	1.28***	0.088***	0.086***	1.88***	2.41***	0.050***	0.027***
Food	0.421***	0.943***	0.225***	0.183***	0.288***	1.70***	0.440***	0.066***
IT	0.410***	0.277***	0.032***	0.035***	0.502***	0.440***	0.045***	0.044***
Miscellaneous	0.310***	0.776***	0.072***	0.322***	0.308***	0.706***	0.088***	0.423***
Service	0.519***	0.252***	0.015***	0.020***	0.865***	0.618***	0.011***	0.015***
Tannery	0.394***	0.925***	0.040***	0.010***	0.406***	0.344***	0.039***	0.047***
Cement	0.446***	0.269***	-0.010***	0.005	0.199***	0.641***	0.077***	0.332***
Ceramic	0.521***	0.332***	-0.017	0.156***	0.220*	0.231**	0.066***	0.181***
	Bearish Market				Crisis Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	0.193***	0.175***	1.40***	1.50***	1.26***	1.57***	0.644***	0.596***
NBFI	1.20***	0.532***	0.410***	0.295***	0.008***	0.373***	-0.001	**-1.23*** **
Insurance	0.247***	0.732***	0.096***	0.530***	0.276***	0.403***	**-0.630***	-0.512
Textile	0.350***	0.908***	0.468***	0.241***	0.233***	0.330***	**-0.736*** **	**-1.03*** **
Pharma	1.02***	0.471***	0.519***	0.015***	0.295***	0.189	-0.397	-0.157
Engineering	0.421***	0.512***	**-0.101*** **	**-0.081** **	0.044***	0.091***	0.408**	0.404***
Fuel & Power	0.947***	0.809***	0.412***	0.383***	0.160***	0.140***	0.660**	**-0.677*** **
Food	0.193***	0.196***	0.210***	0.279***	0.124***	-0.007	0.437	0.075
IT	0.078***	-0.001	0.030***	0.033***	0.107**	0.054	0.790***	0.146
Miscellaneous	0.245***	0.948***	0.075***	0.311***	0.068	0.048	0.676***	-0.284
Service	0.051***	0.503***	0.056**	-0.083***	0.180***	0.027***	0.924*	**-0.220** **
Tannery	0.614***	0.278**	-0.063	0.010***	0.170*	0.042	-0.655	0.313
Cement	0.651***	0.306***	**-0.106*** **	**-0.064*** **	0.039	-0.010	0.378	-0.062

Ceramic	0.722***	0.391***	**-0.078****	**-0.051****	0.065*	0.012	0.594	-0.326
	Extended Crisis Market				COVID-19 Market			
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4
Banking	1.66***	0.928***	0.073***	0.220***	0.007	0.556***	0.857**	-0,089
NBFI	0.277***	0.304***	**-0.815*****	**-0.609*****	0.173	0.743***	0.451***	0.361***
Insurance	0.267***	0.534	**-0.569*****	**-0.962*****	0.526***	2.69***	0.384***	0.262***
Textile	0.222***	0.291**	**-0.500*****	**-0.631*****	1.48***	2.10***	0.521***	0.477***
Pharma	0.542***	0.189	**-1.09*****	-0.139	0.387**	0.162	0.403***	0.455***
Engineering	0.254***	0.246***	**-0.569*****	**-0.281*****	1.95***	3.55***	0.392***	**-0.182****
Fuel & Power	0.122***	0.129*	**-0.259*****	**-0.403*****	0.438***	1.69***	0.375***	0.175***
Food	0.073	0.029	0.185	0.015	0.612***	1.94***	0.620***	0.058***
IT	0.079**	0.041	0.643***	0.217	1.48***	1.10***	0.028	0.033***
Miscellaneous	0.059**	-0.058	0.551***	**-0.292***	0.281	0.521	0.308**	0.410***
Service	0.023***	0.025***	-0.042	**-0.102****	0..497**	-0.219	0.072*	0.168**
Tannery	0.010	0.019	0.184***	0.121	0.868***	0.831	0.083**	-0.099
Cement	0.086***	-0.043**	0.612***	0.173	0.196	0.549**	0.106	0.142***
Ceramic	-0.094***	0.012	0.710***	-0.130	0.017***	-0.220	0.109**	0.186***

Note: ***The coefficient is significant at the 1% level.
** The coefficient is significant at the 5% level.
* The coefficient is significant at the 10% level.

As shown in Table 6.34, the coefficient values of γ_3 and γ_4 are significant and negative only for three industries (engineering, cement, and ceramic) in bearish market. Investors in the insurance industry tend to herd during extreme up market, while non-bank financial institutions, fuel & power, and service industries exhibit herding during extreme down market in crisis period. The textile industry shows evidence of herding when the market experiences extreme movement in both the upper and lower tail of the return distributions. The results confirmed the presence of herding behavior for eight industries in the extended crisis market. The Pharmaceuticals industry unveils herding behavior during extreme up markets, while miscellaneous and service & real estate industries exhibit herding during down markets. However, non-bank financial institutions, insurance, textile, engineering, and fuel & power industries reveal the presence of herding activity during extreme up and down-market movements. It is interesting to point out that the magnitude of herding behavior is much stronger in these five industries than in others. This leads to the belief that investors in these industries are severely concerned about potential losses and tend to follow collective market behavior to avoid risks during extreme market directions. Market participants in Bangladesh equity market do not manifest any herding behavior in the entire and bullish market periods. However, investors in the engineering industry display some herding activity during the COVID-19 pandemic when the market moves in an extremely negative direction.

From the discussion of estimated results reported in Table 6.31 through Table 6.34 we can observe a common pattern in industry herding behavior, which is more industries exhibit herding activity in the extended crisis market compared to other market periods. The possible explanation is that heightened level of uncertainty and information asymmetry may be more prolonged in the equity market. The perceptions and investment behaviors of market participants can be influenced by psychological factors like cognitive biases, fear, greed, social cues, and these may vary across various industries. Therefore, market participants may rely more heavily on the actions of others ignoring their private beliefs in shaping their investment decisions, which may exacerbate herding activity within certain industries in Bangladesh equity market.

6.8.15 Impact of Macroeconomic Shocks and Monetary Policy Shifts on Herding Dynamics

The equity market is a fascinating environment to investigate herding dynamics because of its evolving nature and vulnerability to external shocks. Macroeconomic variables and monetary tools may offer a crucial role in shaping the sentiment of equity market participants on their irrational decision-making process. Examining the interaction between herding behavior and these factors, the current study intends to discover the extent to which macroeconomic variables and monetary policy interventions induce collective investor behavior.

The link between macroeconomic variables and stock market behavior can be theoretically motivated by the contagion theory. It states that any change in a macroeconomic variable may cause an immediate reaction of financial market participants and can affect the correlated behavior (Chang & Rajput, 2018). The arbitrage pricing theory (APT) of (Ross, 1976) develops a theoretical framework that describes how a multifactor structure may explain stock price behavior. The APT theory predicts that when any expected or unexpected new information arrives about macroeconomic fundamentals, it might exert considerable influence on equity market performance using either the discount rate or future expected cash flows or both channels. Two macroeconomic variables that can have an important consequence on the stock market include interest rates and exchange rates. Interest rates can affect stock prices through the discount rate channel. When interest rates change, the required rate of return of investors used to evaluate the present value of future cash flows from stock also changes, which will ultimately impact equity's intrinsic value. According to the capital asset pricing model (CAPM), we can establish a positive association between interest rate changes and the required rate of return on equity investment. Interest rate variations may control equity prices through a portfolio rebalancing effect. When the yield on bonds declines, investors prefer to switch their investment from fixed income securities to equity, pushing up the prices of equity stocks.

A large number of literatures investigated the relation between changes in interest rates and equity market return (Ballester, Ferrer, & González, 2011); (Ferrer, Bolós, & Benítez, 2016); (Ferrando, Ferrer, & Jareño, 2017); (Jareño, Ferrer, & Miroslavova, 2016); (Jammazi, Ferrer, Jareño, & Hammoudeh, 2017); (Morley, 2007); (Moya-Martínez, Ferrer-Lapena, & Escribano-Sotos, 2015).

The relation between exchange rates and stock market performance is described by traditional macro models of an open economy. Theory shows how exchange rate changes affect the international competitiveness of firms and their earnings, which may impact equity prices (Dornbusch, 1980). The depreciation of the local currency facilitates exporting goods more attractive, enhances foreign demand, and hence revenues, which may lead to a rise in equity prices (Gavin, 1989). Another theory that describes the relationship between exchange rate and stock price is the portfolio balance model, which emphasizes the country's capital account transaction. A vibrant equity market would attract capital inflows into the country through increased foreign portfolio investment, which will appreciate the local currency. The opposite will happen in case of a downturn in the equity market where investors would sell their portfolio investments to minimize the losses, and hence capital migrates to other the country. In effect, the local currency will depreciate. The following studies examined the relationship between exchange rates and the equity market (Adebiyi, Adenuga, Abeng, & Omanukwue, 2009); (Agrawal, Srivastav, & Srivastava, 2010); (Chinzara, 2011); (Cho, Choi, Kim, & Kim, 2016); (Hau & Rey, 2006); (Homma, Tsutsui*, & Benzion, 2005); (Gong & Dai, 2017); (Lawal, Somoye, & Babajide, 2016); (Lin & Fu, 2016); (Suriani, Kumar, Jamil, & Muneer, 2015); (Tronzano, 2021); (Yazdani Varzi, Memarian, & Nabavi Chashmi, 2022); (Yadav, Khera, & Mishra, 2022).

Little attention has been given to uncover the impact of macro variables on herding behavior in the equity market. The effects of changes in macro variables and monetary policy tools together on herding behavior may explain the level of equity market efficiency and identify this bias can help investors assess and potentially exploit profitable opportunities. As a frontier equity market, Bangladesh is perceived to be more vulnerable to any macroeconomic shocks and monetary policy shifts. The susceptibility of the market may significantly impact investors' expectations and market sentiment and also provide valuable insights into the equity market dynamics. This study addresses this gap to empirically investigate how these factors influence herding behavior and contribute to the literature in capturing practical insights for equity market participants and policymakers within the framework of a frontier market like Bangladesh.

6.8.15.1 Nexus between Herding Behavior and Macroeconomic Variables

This section makes an inventive effort to examine whether variations in interest and exchange rates exert influence on herding behavior in the Bangladesh equity market.

Table 6.35: Regression results of cross-sectional absolute deviation (CSAD) under changes in macroeconomic variables

In Table 4, the parameters are estimated using the following regressions with AR(1):

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta exr-} R_{m,t}^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta exr-} R_{m,t}^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta int+} R_{m,t}^2 + \varepsilon_t$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_1^{\Delta int-} R_{m,t}^2 + \varepsilon_t$$

Where, $|R_{m,t}|$ represents the absolute value of the equally weighted market returns, calculated using the returns of all listed securities on day t, $R_{m,t}^2$ represents the market returns squared. $D_1^{\Delta exr+}$ represents a dummy variable that takes value one when the local currency (BDT) depreciates (exchange rate increases) and zero otherwise; $D_2^{\Delta exr-}$ represents a dummy variable that takes value one when the local currency appreciates (exchange rate decreases) and zero otherwise; $D_1^{\Delta int+}$ represents a dummy variable that takes value one when the interest rates increase and zero otherwise; $D_2^{\Delta int-}$ represents a dummy variable that takes value one when the interest rates decrease and zero otherwise. We employ a repo rate as a measure of interest rate. The coefficients γ_3 and γ_4 should be negatively significant to confirm herding behavior. Estimation is performed for the overall market (January 2010-December 2021), bearish, and extended crisis (04/01/2010-29/12/2012)). A bearish market is separated using the Dow Theory.

Panel A: Effects of change in exchange rates						Equation
	γ_1	γ_2	γ_3	γ_4	Adjusted R^2	
Overall Market	0.748***	-0.012**	- 0.066***		0.22	6.22
	0.748***	0.053***		0.064***	0.22	6.23
Bearish Market	0.830***	-0.014***	-0.056***		0.23	6.22
	0.831	0.041		0.052***	0.24	6.23
Crisis Market	0.552***	-0.017***	0.062		0.18	6.22
	1.69	-0.227		-0.089	0.19	6.23
Extended Crisis Market	0.987***	0.001***	-0.005***		0.79	6.22
	0.988	0.044		-0.063***	0.83	6.23
Pane B: Effects of change in interest rates						
	γ_1	γ_2	γ_3	γ_4	Adjusted R^2	
Overall Market	0.880***	-0.306***	0.290		0.78	6.24
	0.925	-0.186		-0.085***	0.82	6.25
Bearish Market	0.381***	0.013***	-0.169***		0.76	6.24
	0.378	-0.017		-0.170***	0.88	6.25

Note: ***Significant at the 1% level.
**Significant at the 5% level. The p-values are reported in parentheses
Regression estimation is performed by HAC (Newey-West) approach to correct heteroscedasticity and autocorrelation.
Source: Calculation is conducted by the author with EViews

Table 6.35 furnishes the regression results based on equation 6.22 through and 6.25 in which the effects of variations of two macroeconomic variables on herding behavior are displayed. In Panel A, for the overall, bearish, and extended crisis markets, the estimated coefficient γ_3 is significantly negative, whereas γ_4 is insignificant for all markets. These findings suggest that depreciation of the Taka tends to induce herding behavior in Bangladesh equity market. For crisis market, we do not confirm the presence of an exchange rate impact on herding behavior. Panel B provides the results of changes in interest rates and indicates that the coefficient γ_4 for the overall and bearish markets is negative and statistically significant. The empirical results manifest that the phenomena of interest rate decrease and depreciation of the local currency, have a strong influence on herding behavior in our equity market. We may draw the inference that variations in macroeconomic variables convincingly exert influence on the herding tendency of market participants in the Bangladesh equity market.

6.8.15.2 Nexus between Herding Behavior and the Effects of Monetary Policy

In monetary policy, the interest rate represents the central bank's stance. Studies that have separately investigated the effects of monetary policy shocks on equity returns include (Bjornland & Leitemo, 2009; Bernanke & Kuttner, 2005; Gong & Dai, 2017; Thorbecke, 1997).

In this part, we endeavor to examine the effects of monetary policy on investors' tendency towards herding in the Bangladesh equity market. We analyze the effects of monetary policy in two aspects. One approach is to examine herding behavior around the monetary policy announcement date, and the second approach is to explore herding behavior around changes in monetary policy variables. The effects of monetary policy are investigated with two policy tools: changes in the deposit rate and the deposit reserve ratio.

Table 6.36: Regression results of cross-sectional absolute deviation (CSAD) under the effects of monetary policy shifts

In Table 5, the parameters are estimated using the following regressions with AR(1):

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varphi_j D_j R_{m,t}^2 + \varepsilon_t \qquad \text{(j=1,2,3,4,5)}$$

Where, $|R_{m,t}|$ represents the absolute value of the equally weighted market returns, calculated using the returns of all listed securities on day t, $R_{m,t}^2$ represents the market returns squared. D_1 to D_4 represent dummy variables that take value one in a month when the deposit rates increase, the deposit rates decrease, the deposit reserve ratio increases, and the deposit reserve ratio decreases, respectively and zero otherwise; D_5 represent a dummy variable that takes value one during monetary policy announcement month and zero otherwise. The coefficients φ_1 through φ_5 should be negatively significant when monetary policy tools have an impact on herding behavior. Estimation is performed for the overall market (January 2010-December 2021), bearish, and extended crisis markets (04/01/2010-29/12/2012). A bearish market is separated using the Dow Theory.

	γ_1	γ_2	φ_1	φ_2	φ_3	φ_4	φ_5
Overall Market	0.375***	0.023**	-0.164				
	0.783***	-0.013***		0.165			
	0.728***	0.103*			-0.116**		
	0.402***	0.013***				-0.023***	
	0.403***	0.012***					-0.046***
	γ_1	γ_2	φ_1	φ_2	φ_3	φ_4	φ_5
Bearish Market	0.934***	-0.415	0.398				
	0.381***	0.013***		-.172***			
	0.386***	0.013***			-0.029***		
	0.819***	0.085*				-0.099**	
	0.395***	0.013***					-0.048***

	γ_1	γ_2	φ_1	φ_2	φ_3	φ_4	φ_5
Crisis Market	0.506***	0.056	-0.112				
	0.506***	-0.04**		0.114			
	0.550***	-0.060**			-0.004		
	1.63***	-0.245				-0.009	
	0.542***	-0.057***					-0.006
	γ_1	γ_2	φ_1	φ_2	φ_3	φ_4	φ_5
Extended Crisis Market	1.00***	0.352**	-0.370**				
	0.448***	0.012***		0.032			
	0.491***	0.011***			-0.034***		
	0.498***	-0.028***				0.038***	
	0.505***	0.010***					-0.059***

Note: *** Statistically significant at 1%
** Statistically significant at 5%.
* Statistically significant at 10%
Regression estimation is performed by HAC (Newey-West) approach to correct heteroscedasticity and autocorrelation.
Source: Calculation is conducted by the author with EViews

Table 6.36 discloses the results of the impact of monetary policy tools on herding behavior. The empirical findings communicate that an increase in the bank deposit rate does lead to herding behavior only for the extended crisis market since φ_1 is negatively significant, whereas a decrease in the deposit rate does influence herding behavior for the bearish market. The estimated results stipulate that both increases and decreases in the deposit reserve ratio significantly influence herding behavior in the overall, bearish as well as in the extended crisis markets as evident by the negatively significant coefficient of φ_3 and φ_4, respectively. Like the deposit reserve ratio, similar results are observed in the case of monetary policy announcement date since the coefficient of φ_5 is negatively significant for all markets except the crisis market.

Our findings further reveal that a decrease in the policy interest rate has a substantial influence on herding behavior in the overall and bearish market phase. This finding can be understood by investor psychology and the theory of monetary transmission. In general, a decline in interest rates reduces the opportunity cost associated with equity holding, which may indicate a more accommodative monetary policy. However, such an indicator might trigger investors to overreact in a pessimistic market condition, like the bearish market. Market movements caused by policy changes may lead investors to herd instead of making independent valuation-based decisions. our results are aligned with empirical studies, which state that expansionary monetary policy may result in investor optimism and collective trading behavior (Balcilar, Demirer, & Hammoudeh, 2013).

The study, beyond our macroeconomic analysis, analyzes whether and to what extent monetary policy tools impact herding dynamics in Bangladesh equity market. The results show that any rise in bank deposit rate may trigger herding in the extended crisis market, whereas a decrease in deposit rate seems to induce investor herding behavior in the bearish market. These herding trends may reflect investor sensitivity to alternative investment vehicles during high market uncertainty. When deposit rate increases during a prolonged market crisis, risk-averse investors may take safe refuge in bank deposits, leading to correlated withdrawals from equity investments - a form of reverse herding that still manifests in aggregate levels. Alternatively, investors may interpret a reduction in the deposit rate in bearish markets as a stimulus policy signal, encouraging synchronized re-entry into equity markets, amplifying herding. Our findings also indicate that both increases and decreases in the deposit reserve ratio- a base liquidity regulating monetary tool, strongly induce herding tendencies of investors in the overall as well during bearish and extended crisis markets. This bidirectional effect implies that market participants interpret both contractionary and expansionary monetary policy changes as signals of impending market conditions, triggering coordinated trading. This is consistent with behavioral finance's concept of signal-extraction problems, in which heterogeneous investors are prone to overreacting to policy announcements when they only have limited information processing capacity and tend to infer market sentiment from central bank actions (Scharfstein & Stein, 1990).

Further, the analysis demonstrated that monetary policy announcement dates themselves are associated with significant herding effects in the same market states (overall, bearish, and extended crisis) underscores the significance of announcement timing and communication strategy. During monetary policy announcement days, investors may pay more attention, resulting in increased uncertainty and prompting synchronized decision-making particularly in less-efficient markets. This result is in line with empirical findings indicating that central bank communication may shape investor market expectations and behavioral motivation beyond the actual policy changes (Ehrmann & Fratzscher, 2007).

6.8.16 Associating Behavioral Responses and Macroeconomic Shocks.

The macroeconomic shock analysis and the monetary policy variables point out the way investor behavior within the frontier markets is responsive not only to the market shocks, but also the general policy and economic setting. Financing costs and market uncertainty are usually increased by increases in policy interest rates or reserve tightening, which will induce more investors to follow the crowd instead of making an individual valuation - the similarity of the effect of sentiment-driven herding under policy pressure. On the other hand, stability of exchange rates or expansionary monetary policy can give temporary solace to the investor’s confidence so that, imitation is not necessary.

These findings indicate that the processes of herding in the Bangladesh equity market are, to some degree, an adaptive reaction to macroeconomic volatility: where the policy indicators are unclear or not anticipated, and investors follow the collective behavior as a heuristic behavioral motivation. The causal connection is therefore in the exhibition of macro shocks into the perceived uncertainty leading to collective trading and short-term consensus. This process reiterates the findings that herding behavior may become a behavioral phenomenon of macro-financial cycles in frontier markets context.

6.9 Conclusion

The essay attempts to provide a thorough examination of the empirical soundness of the market participants herding effect in the Bangladesh equity market in relation to the different market conditions such as bullish, bearish, crisis, extended crisis, and COVID-19 markets. In this thesis, we used both Christie & Huang's (1995) CSSD and Chang et al.'s (2000) CSAD dispersion measures to examine herding behavior. The analytical findings of the work give complicated dynamics of herding that interfere with the conventional interpretations and provide the distinctive dynamic of a frontier market setting.

Herding behavior is not occasional rather it is persistent and pervasive in the Bangladesh equity market depending on the different equity market conditions as well as market states. The analysis of herding during the extremes market movement at the outset showed no significant evidence. Nonetheless, when the dummy variables model is modified to include the extent of the market returns in its tail distribution; we observe herding behavior in the overall market, bearish, and extended crisis markets, particularly in the extreme downward movements. This alteration examines how the model is sensitive to the strength of market movements in exploring potential herding detection during extreme market downturns.

Analysis of the non-linear relationship in the CSAD model points to the fact that herding took place only in the crisis market, a fact that indicates imitating the behavior of other investors, disobedience to their own choices. This observation is in line with the early research by Clements et al. 2017; Economou 2020; Li et al. 2018; Litimi 2017; Ouarda et al. 2013; Shah et al. 2017) and validates hypothesis 5 that the herding exists in the crisis period. However, under the CSSD model, herding exists in the overall, bearish, and extended crisis markets. This implies that investors tend to be more group oriented in situations of increased risk aversion or bad market sentiment, which is consistent with behavioral finance theory. This observation generates one important implication the CSSD model seems to encapsulate more effectively than the CSAD model. CSSD is more sensitive to extreme dispersion of returns and can be more appropriate in detecting imitating trading behaviors. Herding effects are more significant than bearish and crisis market conditions, which confirm hypotheses 3 and 5.

The thesis investigates the possible asymmetric herding behavior of investors based on various market dimensions such as positive (negative) returns, high (low) trading volume and high (low) market volatility. In addition, the study also analyzes volatility, which further defines the strengths of two measures of dispersion. In the CSAD model, the presence of asymmetric herding is demonstrated in the high volatility state of the crisis market, and in the overall, bearish, and extended crisis market with the CSSD model.

Among new discoveries the thesis reports that the herding tendencies of investors were vehement and very common in the entire and bearish markets during the periods of abnormally high volumes of trading, and in the entire, bear and extended crisis, and the COVID-19 markets during the periods of abnormally high market volatility. The other outstanding finding to the Bangladeshi equity market is that the herding effect was only present in the COVID-19 market when market volatility was extremely high. The very large volumes of trade can indicate a good spirit of time among investors in market and lead to herding by following the majority. Conversely, a very high volatility could indicate the turbulence of the market, where the market players are obliged to find safety through a collective response to the market dynamics.

The other novelty of the research is that the CSSD is more effective than the CSAD measure in revealing the latent herding behaviors of investors within a frontier market. We also point out that the application of the Dow Theory to determine the bullish and bearish phases have helped in making our herding analysis methodologically rigorous.

The CSSD and CSAD results indicate that the herding in Bangladesh is mostly irrational or sentiment-oriented, but not informational. The rational model assumes that investors imitate others since they deduce personal information on trades, which has the potential to improve efficiency in the market. The identified herding patterns, however, are present primarily during the moments of market stress, very volatile situations, and a high level of uncertainty- the conditions in which information is limited, and every emotional response is predominant. The concentration of trades that is experienced in bearish and crisis markets and the lack of herding in bullish markets suggests that investors are responding to fear and loss aversion and uncertainty conditions instead of low-quality private information.

This fact is important since irrational herding impairs price discovery operations and may lead to increased volatility, as rational herding would typically vanish by information being leaked. The observed continued herding of long crisis market and COVID-19 market is thus a psychological conformity effect, which proves that it is collective sentiment, not information efficiency that motivates investor coordination during a frontier market environment.

The structural breaks analysis offers some interesting information on how the key market changes and reforms of the regulatory policy influenced the investor herding behavior within the Bangladesh equity market. The rare COVID-19 has high potential of herding, which is an indicator of increased conformity of the investor in the face of severe uncertainty about the markets. On the other hand, the short-reform and medium-reform structural breaks did not confirm any herding effects. However, herding behavior was statistically significant in the long-term structural reform window, which underscores that regulatory market reforms might take a long enough time to influence investor psychology. All in all, the current results show that exogenous shock may have short-term herding effects, but the effect of regulatory reforms on investor behavior build up over time, which has implications on the role of persistent policies of reform in collective decision-making and equity market discipline.

The industry-level analysis confirms that herding in the Bangladesh equity market is highly state-dependent and fear-based and is observed to manifest strongly during bearish market conditions, crisis situations, and during extended crisis situations but not in bullish markets and the COVID-19 market. Although only the cement industry shows herding during the entire market period, additional industries such as service and real estate, ceramic, non-banking financial institutions, insurance, textiles, fuel and power, and engineering, are characterized by the behavior during stress conditions, especially in extended crises when uncertainty and information asymmetry is more rampant. These findings indicate that industry-level herding is primarily triggered by panic, risk aversion, and negative market news, which underscores the importance of having a tighter regulation regime and transparency in the information to reduce the destabilizing herd behavior during market stress.

The industry-level analysis shows that herding behavior in Bangladesh equity market is extremely state-dependent instead of being persistent in all market conditions. Although herding is evident in the cement industry throughout the entire life of the market, other industries also tend to behave in that way when they are under stress. Specifically, bearish markets also display herding in a limited number of industries, including service and real estate, cement, and ceramic, but when it comes to periods of crisis or extended crisis, the wider herding occurs, including non-banking financial institutions and insurance, as well as textile, fuel and power, and engineering.

The lack of herding in bullish and COVID-19 markets also highlights the fact that fear-related herding is predominant in investor herding in Bangladesh, as opposed to optimistic-related herding, which is associated with increased uncertainty, panic, and negative news in recessions. The important lesson is that herding is more strongly reinforced during extended periods of crisis conditions than during any other market conditions, and that permanent information asymmetry and the presence of persistent uncertainty support the behavior of aggregation of industry behavior to investors.

The results of the frontier equity market in Bangladesh are consistent with findings in other markets. Similar works on the Nigerian, Vietnamese, and Kenyan stock markets (e.g., Bouri et al., 2021; Hoang and Nguyen, 2020; Kiptoo et al., 2019) also reveal the same problem, where herding only increases during crises and a time of macroeconomic instability, which is mainly due to retail domination and information asymmetry. Nonetheless, in comparison with these markets Bangladesh exhibits a more enduring type of fear-based herding that spills out to longer crisis phases, implying that institutional uncertainty over time and the lack of institutional engagement enhance conformity to behavior.

Placing the findings in the wider frontier-market context, the thesis will provide a contribution to the literature on cross-country behavioral finance, demonstrating that, although the direction of herding is universal, i.e. stronger in the recession period, the level and the duration of herding in

Bangladesh are relatively high. This highlights the need to put into consideration the institutional maturity, information transparency, and policy credibility in generalizing behavioral patterns among frontier economies.

These results confirm that the herding in Bangladesh equity market is not homogeneous but rather clustered in industries and in the periods when risk and uncertainty are high. This carries significant consequences to regulators and policymakers because controlling the mood of the investor and enhancing information disclosure could help prevent destabilizing herd behavior at a turbulent stage in the market.

Chapter Seven- Conclusion: Synthesization, Contributions, and Policy Implications

7.1 Introduction

The overall findings of the thesis, which are based on the disposition effect, herding behavior, and overconfidence bias, are synthesized in this chapter and explained in the cumulative theoretical, empirical, and policy implications perspectives in the Bangladesh equity market. The thesis was aimed at investigating the existence and functioning of fundamental behavioral biases recorded in both developed and emerging markets within a framework of frontier equity market characterized by low liquidity, information asymmetry, and periodic crises. The chapter ends with a discussion of limitations and providing specific research paths that can be pursued in the future.

7.1.1 Alignment of Research Questions and Individual Essay Chapters

Three behavioral bias chapters directly respond to their individual research questions.

Chapter 4 that analyses the disposition effect addresses the first research question by using abnormal trading volume analysis and several statistical tests to prove that every investor sells winning stocks at a slower rate and retains losing stocks at a slower rate. The chapter shows how this kind of behavior is maintained across the market states and thus confirms the existence of disposition effect characterized by loss-aversion.

Chapter 5 provides the solution to the second question which is whether market returns predict future trading volume using a multi-method approach - VAR, Transfer Entropy and LSTM models. This chapter empirically establishes the overconfidence bias and presents a new theoretical extension (defensive overconfidence) that takes place when a market is driven by crisis.

Chapter 6 answers the third research question in detail by assessing herding behavior based on CSSD, CSAD, non-linear models, quantile regression and structural break analysis. This chapter determines the time and reason behind collective investor movement, particularly in the bearish, crisis, and extended crisis markets, which validates that there are asymmetric and state dependent herding tendencies in Bangladesh.

The three empirical chapters are a direct answer to the research questions as they present a single explanation of behavior explaining how disposition effect, herding behavior, and overconfidence bias are joint in their influence on investor decision-making in a frontier equity market.

7.2 Synthesization of Empirical Findings

This thesis gives a combined explanation of three underlying behavioral biases; disposition effect, herding behavior and overconfidence bias in the environment of Bangladesh stock market, a frontier market which can be defined as having structural reforms, shallow market and inefficient information. Through these behavior patterns in various market conditions which include bullish, bearish, crisis, protracted crisis and COVID-19, the study provides a state-contingent behavior model which connects investor psychology to market dynamics, institutional conditions and macroeconomic factors.

The overall results indicate that behavioral biases are not new or novel and exist in all market conditions over time, but the magnitude and expression of these biases are different to the conditions in the market. The disposition effect is always evident in the aggregate market and in the bullish market, crisis and extended crisis market, which highlights the long-term nature of loss aversion and the urge of investors to realize gains in time. The analytic of the herding behavior shows that the movement of collective investors is extensive but asymmetric; that is, it is highly accentuated during extreme periods of the market returns, volume, and volatility. The herding is enhanced in the bearish and prolonged crisis and another factor that promotes the herding is the macroeconomic factors like the depreciation of the exchange rate and the falling interest rates. The liquidity inducing tools hence monetary policy can greatly influence the level of herding and this implies that the investor sentiment in Bangladesh is in response to the policy tool and macro indicators.

The analysis of overconfidence represents strong and state-sensitive behavioral patterns across three models- VAR, Transfer Entropy, and LSTM, reinforcing that it is common in overall and crisis-driven market states. The development of a new behavioral phenomenon, defensive overconfidence, is the manifestation of the change in investor psychology under the pressure of the market changing the optimistic trading into the protectionist one. This pattern of behavioral change implies how investor cognition is changing in the face of uncertainty.

In a frontier market context, the integrative results illustrate that investor actions are not random or integrated; instead, they are systematically influenced by market conditions, structural reforms, and macroeconomic and monetary policy shocks. The documentation of behavioral biases even in the course of extensive market reforms implemented by regulators implies that all structural changes cannot completely get rid of psychological biases. Rather, it is investor education and regulatory scrutiny along with behavioral-sensitive policy formulation necessitate significance to the improvement of market efficiency.

The thesis brings unified insights into methodological advancement to behavioral finance by the application of econometric model along with, information-based entropy, and advanced machine learning technique. This novel approach is better equipped with exploring complex, non-linear, adaptive, and state-dependent nature of investor behavior in the Bangladesh equity market. Conceptually, it introduces "defensive overconfidence" and systematically classifies market states applying Dow Theory**,** offering innovative perspectives on how investor sentiment interacts with different equity market phases in the context of frontier markets.

In aggregate, the investigation of these three biases an empirically based and theoretically augmented insight into the investor psychology in the Bangladesh equity market. It confirms the fact that behavioral biases are inherent characteristics of market development, and the evidence of their prevalence across various market states, particularly in stress-driven environments, reinstate human cognition, and structural and behavioral market dynamics. These findings can be used to understand behavioral finance and also to determine effective regulatory and policy frameworks to enhance market stability and rationality among investors in a frontier market like Bangladesh.

7.3 Major Empirical Findings Contributing to Behavioral Finance Literature

The thesis analyzes the three basic behavioral biases from the perspective of frontier equity market, which is a novel development to behavioral finance literature.

The systematic classification of the Bangladesh equity market into different market states including bullish, bearish, crisis, extended crisis, and COVID-19 where Dow Theory is applied to identify the bullish and bearish market patterns, offers a dynamic framework in existing literature. This novel approach brings significant value addition to the depth and contextual validity of the empirical findings, especially in the context of frontier equity markets.

Analyzing investor herding tendency utilizing the CSAD and CSSD measures of return dispersion and their modification under conditions of extreme market returns, trading volume and market volatility; integrated with quantile regression, enriches the holistic nature and robustness of the findings. Innovative non-linear information theoretic measure of transfer entropy, and advanced deep learning Long Short-Term Memory (LSTM) models were adopted in investigating overconfidence bias, contributing significantly to analytical enhancement of behavioral finance research.

The persistence of herding behavior and overconfidence bias at industry analysis in frontier market environment further strengthens and broadens the behavioral finance research. In addition, the results on the overconfidence essay develop a new dimension to its theoretical advancement, termed defensive overconfidence. The discovery of this behavioral pattern reinforces that investors tend to continue excessive trading during stressful periods despite negative market movements, perhaps due to the illusion of control.

Long-term structural break analysis on herding behavior implies that long-term policy interventions and sustainable reform initiated by regulators after market crash, have crucial influence on reshaping investment behavioral dynamics in the Bangladesh equity market.

7.3.1 Theoretical Behavioral Finance Contributions.

In addition to being empirically verified, the thesis makes a number of contributions to the behavioral finance theory.

To begin with, the validation of the disposition effect in several market states enhances predictive validity of Prospect Theory, especially loss-aversion and mental-accounting aspects. The state-dependency of the effect shows that the reference points and risk preferences of investors change in different market conditions and provide empirical generalization of the dynamic framing of Prospect Theory.

Second, herding behavior documented in extreme market conditions contributes to the behavioral asset pricing models such that return dispersion and price volatility in frontier markets are not entirely due to fundamentals but a collective psychological reaction. It is consistent with and builds upon the existing literature regarding sentiment-driven pricing anomalies by indicating that collective market dynamics, but not necessarily individual decision errors can be systematically tracked by asset mispricing in frontier markets.

Third, the concept of the introduction of defensive overconfidence is a new theoretical creation. In contrast to traditional overconfidence in rising markets, defensive overconfidence appears at the time of crises and recessions, as a psychological defense mechanism, in which investors remain aggressive in their trades to re-establish their perceived control. This action shows a previously unstudied aspect of investor cognition the way overconfidence is changed in times of stress, and it has a direct contribution to the development of the behavioral models of risk-taking.

All these contributions add value to the behavioral theories already in existence by showing that the psychology of investors in frontier markets is adaptive, state-dependent, and influenced by institutional fragility, information asymmetry, and macroeconomic uncertainty.

7.4 Thesis Practical Implications

The results of the thesis highlight the paramount role of investor psychology in determining a market outcome, especially when it interacts with different market states and structural phenomena in the Bangladesh equity market. The dynamics of these behaviors can be useful to regulators, policymakers and market participants who need to improve market efficiency and stability. The evidence indicates that in times of increased uncertainty and stress there is too much trading activity by investors, even when the market moves in an adverse manner, this is probably influenced by an illusion of control and overconfidence.

Such behavioral patterns presuppose the necessity of specific policy actions that might enhance the level of investor awareness, financial literacy, and risk perception. Regulatory bodies such as The Bangladesh Securities Exchange Commission (BSEC) can take the opportunity of constructing behaviorally sensitive market regulations and communication policies to reduce irrational trading in volatile markets. For example, an understanding of the continuity of behavioral bias means that market-stabilizing mechanisms must use behavioral aspects, as opposed to using only the assumptions of rational markets. The conditions that increase herding, panic selling and excessive trading can be alleviated through policies like circuit breakers, better disclosure standards, better corporate governance and real time monitoring of the market. In addition, increasing market transparency, dissemination of information, and corporate governance can be employed to mitigate information asymmetry, which is a primary contributor to heightening behavioral biases in frontier markets. The regulators can alleviate information asymmetry by carrying out specific training using workshops or certificate-based training in order to make critical information of the market easily accessible. They will be able to control the activities of the market by introducing trading platforms based on technology that would allow them to oversee the market actions and control speculative trading.

The reported sensitivity of investor behavior to macroeconomic shocks provides policy makers with the significance of effective and predictable monetary and fiscal communication.

Uncertainty in policy signaling can be directly undermined to reduce sentiment-driven market responses.

Presence of behavioral biases could be indicative of price distortion in the equity market. These market anomalies can be easily exploited by investors to make proper decisions on investment. They can either go on action to hedge against a negative market or devise some sort of contrarian action and go opposite to the direction taken by the market. Apprehending these behavioral intuitions, investors will manage to remain motivated with investments over long term rather than rushing to short term market opportunities. It is imperative to incorporate behavioral finance lessons into the curriculum of investor training programs. Bias recognition, long-term portfolio discipline, risk perception, and decision making under uncertainty programs could assist the retail investor to avoid psychologically induced errors.

Therefore, the thesis does not only contribute both empirically and theoretically but also offer practical knowledge that can be used to enhance behaviorally conscious market policies and investor education approaches that are expected to improve market stability and investor welfare.

7.5 Thesis Limitations

The empirical works on three-essay represent an inclusive data on all listed common stock in the Dhaka Stock Exchange, it omits mutual funds and bonds that could give a specific demonstration of the investor behavior. The analysis of these behavioral biases is based largely on aggregate market-level and industry-level data, which ignores any stock-specific dynamics that could be used to identify the behavioral trading patterns of institutional investors. The absence of individual brokerage house data may constrain the capability of the research to generate findings about investor heterogeneity in the equity market. In addition, the findings are specific to only Bangladesh market and exclude the cross-country examination with other frontier equity markets, which may produce generalizability of the findings

7.6 Future Research Direction

The future research on behavioral biases may focus on investor-level data, and investor sentiment index in the Bangladesh equity market to examine whether heterogeneity of individual investor accounts as well as investor types like retail and institutional may influence these biases.

The empirical studies on these behavioral biases can also be performed in other frontier equity markets to assess whether the biases strongly present in the Bangladesh equity market can hold in other markets. Researchers may extend the examination of these behavioral biases on an experimental basis to capture how investors react to a controlled market framework rather than using historical information.

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