UNIVERSITY OF GHANA

OVERCONFIDENCE BIAS OF INVESTORS' INVESTMENT DECISIONS ON GHANA STOCK EXCHANGE

BY

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DECLARATION

I, Raphael Kuranchie-Pong, do hereby declare that this work is the result of my own research and has not been presented by anyone for any academic award in this or any other university. All references used in this work have been fully acknowledged.

I bear sole responsibility for any shortcomings.

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CERTIFICATION

I hereby certify that this thesis was supervised in accordance with procedures laid down by the University.

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Dr. LORD MENSAH (Date)
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DEDICATION

This work is dedicated to the Almighty God for His grace, my parents, Mr. John Kuranchie-Pong and Mrs. Mary Kwantwi, to Brig. Gen. Adokpa and all my siblings for their love and supports.

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ABSTRACT

The Efficient Market Hypothesis (EMH) postulates that all publicly available information on any firm's stock future performance is incorporated in the firm's stock price such that the actual price of the stock is equal to its intrinsic value. The EMH is argued to lead to "correct prices" which creates the necessary environment for efficient allocation of economic productive scarce resources. The documentation of empirical evidence of weak-form inefficiency on most stock markets especially Africa, has received much attention by regulators, researchers, investors and many other players in the financial industry. The Ghana stock market, for instance, is documented in the literature to be weak-form inefficient.

In this study, the researcher turns to behavioural finance to test the rationality of the investors on Ghana stock market since the rationality assumption is one of the pillars upon which market efficiency is built. To test the rationality of the market participants, overconfidence behavioural bias is used as a conditional rationality test proxy. The concentration on overconfidence bias does not suggest that overconfidence is the only bias worth considering but it is due to the fact that it is reported in the literature to be one of the robust psychological behavioural biases.

Overconfidence is the act of having a mistaken assessment and believing in these assessments too strongly. To test the overconfidence bias, a market-wide Vector Autoregressive (VAR) model and its associated impulse response function is used to investigate the lead-lag relationship between market returns and market trading volume. Also, granger-causality test was performed to test the causality between returns and trading volumes. This study uses the Ghana Stock Exchange All-Share index (GSE-ASI) and the Ghana Stock Exchange Composite Index (GSE-CI) monthly returns data. In addition, the monthly trading volume,

monthly returns volatility, interest rate and inflation data from 2000 to 2015 are used for the study.

The findings reveal a significant impact of past market returns on current trading volumes. The impulse response function analysis also showed that the response of trading volume to a shock of market return residual remains highly positive and significant at lag one and two. The granger causality reveals unidirectional causality running from returns to trading volumes. The empirical findings finally demonstrate that market participants on GSE exhibit conditional irrationality (overconfidence bias as proxy) in their investment decisions.

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LIST OF ABBREVIATIONS

BOG	-	Bank Of Ghana
EMH	-	Efficient Market Hypothesis
GSE	-	Ghana Stock Exchange
GSE-ASI	-	Ghana Stock Exchange All-Share Index
GSE-CI	-	Ghana Stock Exchange Composite Index
HP	-	Hodrick-Prescott (1997) Filter
MDLTVOL	-	Monthly Detrended Logged Trading Volume
MRET	-	Monthly Index Returns
MSIG	-	Monthly Volatility
VAR	-	Vector Autoregressive

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

In the literature, the nexus between economic growth and financial markets are demonstrated and established in both theoretical and empirical grounds (Beck & Levine, 2004). Financial markets such as capital markets play a very significant role in the building of the financial systems and development of economies. The 2008 global financial crisis which originated in USA and spread globally is a typical example of the impacts of financial markets on the world at large. As a result, financial markets have become one of the key areas of study by researchers and practitioners with focus on both advanced and emerging markets.

The Efficient Market Hypothesis (EMH) is one of the fundamental building blocks of standard finance for understanding financial market activities. A capital market is efficient if asset prices observed on the market fully reflect all publicly available information. This implies that in an efficient market, information processing is done rationally in such a way that no systematic errors are done and significant information is not discarded. As a result, financial asset prices are claimed to be equal to the intrinsic value of the asset since all available public information are incorporated into the asset price during the price formation. Therefore, asset prices are said to be “correct”. Jensen (1978) argues further that in financial settings where information accessibility comes with a cost, the market is said to be efficient when prices of securities reflect information to the level where the marginal benefits of employing the information is not greater than the marginal cost of obtaining the information. It is worth stating that the EMH is built on perfect market assumptions which include no transaction costs, information is costless, homogenous expectations of investors and rationality of market participants.

According to Fama (1970), for an economy to derive optimal benefit from capital market in the form of capital allocation, the capital market must be efficient. A firm performance is measured by its profitability and to a large extent, its efficiency. The society votes in terms of their purchasing power on the markets for a product to some extent determine the profitability of the firm which also directly affects the performance of the firm. The performance of the firm then influences the price of the firm's security. It is worth indicating that a firm's security price would reflect its present and future performance if the market is efficient. This implies that under efficient market, security prices are formed efficiently. Therefore, investors identifying profitable future performance of the firm would invest in such a firm.

Thus, indirectly the society's scarce resources are channelled to productive sectors of the economy. This implies that the efficient allocation of resources in any economy to a large extent depends on the efficiency of the capital markets. On the other hand, if security prices are inefficiently formed, it would lead investments to inappropriate sectors of the economy which would cause a severe social cost to the economy. Thus, there is an established link between capital market efficiency and economic efficiency in resource allocation. According to Fama (1970), an efficient market is a necessary condition for efficient allocation of scarce economic resources in any economy. Fama (1970) states that:

> The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource

> allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that securities prices at any time "fully reflect" all available information. A market in which prices always "fully reflect" available information is called "efficient".
> (Fama, 1970, p. 383)

As a result, over the past six decades, researchers have focused on testing and explaining efficiency of financial markets. In testing the market efficiency, some researchers test the EMH prediction to ascertain whether: asset prices move as random walk over time is true; information is rapidly incorporated into asset prices so that current available information cannot be used to predict future excess returns; technical analysis does not yield excess return; fund managers do not beat the market; and asset prices remain at levels consistent with economic indicators. However, research over the years has shown that most financial markets including emerging markets are inefficient and characterized by many anomalies such as excessive volatility, high trading volumes, market bubbles and crashes, calendar, fundamental and technical anomalies. Yakob, Beal & Delpachitra (2005) for instance employed data from ten Asian markets and documented the existence of seasonality effects. Similar results are also reported on the African stock markets which Ghana stock market is no exception. For example, Appiah-Kusi & Menya (2003), Dewotor & Gborglah (2004), Simons & Laryea (2006) and Mensah, Bokpin & Owusu-Antwi, 2016 reported market inefficiency and calendar anomaly on some African stock markets.

Notwithstanding the benefits of efficient market, the evidence of inefficiencies and anomalies on some equity markets have caused researchers to dive into the possible reasons for such happenings. Thus, a more convincing and extensive way of thinking and understanding the behaviour of market participants, financial markets and the whole society at large became intense. As a result, academic discussions shifted from standard finance theories to the application of human psychology to finance to test the validity of the market participants rationality assumption of efficient market hypothesis. This led to the birth of Behavioural finance.

Behavioural finance researchers and practitioners argue that human psychology and behaviour plays an active role in modelling, analysing and understanding financial markets since both are inherently related. It is worth pointing out that behavioural finance emerged partly from the doubts and qualms about the validity of the assumptions of the standard finance theories. Several psychological findings reported in the psychology and finance literature demonstrate that market participants do not always act in a rational manner but rather are victims of cognitive and emotional biases. These biases lead to deviations from the predictions of standard finance theories. Behavioural finance theories claim that if the assumptions of rationality of economic agents are relaxed, many of the financial puzzles and anomalies would be better understood. Some behavioural biases observed on equity markets such as disposition effect and overconfidence bias are documented to explain some of the inefficiencies and anomalies observed on the markets.

Overconfidence bias is cognitive psychological bias phenomenon occurring when market participants are too confident and exaggerate their own skills and abilities in selecting securities and portfolios as well as predicting securities future returns (Grinblatt & Keloharju, 2009). Research has shown that overconfidence bias of market players is the reason for some of the inefficiencies documented on the financial markets. Overconfidence bias of investors is documented to cause underreaction and overreaction of stock price to public information which leads to short and long run autocorrelation of returns. Overconfidence of market participants is also documented to lead to excessive trading (Odean, 1998). Research have also shown that overconfidence bias of traders on financial markets contribute to excessive volatility observed in financial markets (Chuang & Lee, 2006). Akerlof & Shiller (2010) and Authers (2010) argue that overconfidence of market participants is one of the major variables that trigger beliefs change of market actors and offers the necessary environment for the various market anomalies being observed on financial markets. Therefore, is it possible that the documentation of inefficiency and anomalies on Ghana stock markets are as a result of behavioural biases of the market participants?

1.2 Problem Statement

Efficiency of stock markets have been tested on most markets, both developed and emerging markets and the discussion around it is still very vivid. Testing of efficiency of a market provides vital information as to whether market security prices are always "right". The Bulk of these empirical testing of markets efficiency is conducted on developed markets and mixed results are reported (Mobarek & Keasey, 2000 (cited in Dickson, 2015)). For instance, Choudhry (1994) provided empirical evidence to support market efficiency whiles Lo & MacKinlay (1988) also provided empirical evidence of non-random walk of security prices and as a result reject the market efficiency hypothesis.

African equity markets are characterized by small market size and less liquidity as compared to developed markets. A vast number of empirical studies have been conducted on African equity markets as well to test its efficiency. However, there are mixed empirical results on African stock markets' efficiency. Some of these empirical results reported weak-form efficiency (Appiah-Kusi & Menya, 2003) and others have also reported weak-form inefficiencies (Appiah-Kusi & Menya, 2003; Simons & Laryea, 2006). Some researchers argue that the efficiency of African stock markets progressively change over time (Jefferis & Smith, 2005). Also, quite a number of studies on African equity markets (Alagidede & Panagiotidis, 2009; Aly, Mehdian & Perry, 2004) have reported the existence of calendar anomalies. However, no empirical possible reasons have been provided for such phenomena on equity markets in Africa.

Ghana stock market was judged as the best performing market in the world by the end of 2003 (Adjasi, Harvey & Agyapong, 2008). However, most empirical evidences on Ghana Stock Exchange indicate inefficiencies and anomalies on the market. A vast number of empirical studies to test GSE efficiency have been conducted over the years. Magnusson & Wydick (2002) using eight African equity indices which included Ghana investigated their efficiency by employing partial autocorrelation from 1989 to 1998. Appiah-Kusi & Menya (2003) also used eleven African equity markets including Ghana to test the weak-form efficiency in these markets by employing EGARCH-M model with thin trading correction. Dewotor & Gborglah (2004) employing serial and cross-sectional correlation tests investigated the efficiency of Ghana stock market using daily, monthly and yearly data. Also, Ayentimi, Mensah & Naa-Idar (2013) also examined the weak-form market efficiency on the Ghana stock market. The findings of all these empirical studies unanimously reported that the Ghana stock market is weak-form inefficient. However, these studies do not provide any empirical possible reasons for the inefficiency being observed on GSE.

Also, studies by Alagidede & Panagiotidis (2009) and Mensah et al. (2016) have all indicated the presence of calendar anomalies specifically day of the week effect on Ghana stock market. Dickson (2015) applied Variable Moving Average (VMA) technical trading strategies on the Ghana Stock Exchange Composite Index (GSE-CI) to ascertain whether it would be profitable and outperform the buy-and-hold strategy. Dickson (2015) reported that VMA generated positive returns and four out of the five VMA employed outperformed the results from buy-and-hold rule. These empirical evidences also shows that the GSE market is inefficient and they do not provide any empirical reasons for such phenomena.

In addition, there are many empirical studies demonstrating a relationship between macroeconomic variables and Ghana stock market performance. For instance, Issahaku, Ustarz & Domanban (2013) employed monthly data from 1995 to 2010 to examine the presence of causality between macroeconomic variables and stock returns in Ghana. They used Vector Error Correction (VECM) model and Granger causality for this study. They reported short run and long run relationship between stock returns and macroeconomic indicators. Other studies reporting a nexus between stock performance and macroeconomic indicators on Ghanaian market include Antwi, Ebenezer & Zhao (2012), Kuwornu (2012) and Kyereboah-Coleman & Agyire-Tettey (2008). The empirical evidence of nexus between stock returns and macroeconomic indicators imply the existence of arbitrage profit opportunities which is contrary to the inferences from EMH that stock returns could not be predicted. Also, these studies also do not provide any empirical reasons for these market inefficiencies documented on the Ghana stock market.

In order to improve the efficiency on Ghana stock market, GSE authorities introduced automation trading platform system in 2011. Mensah, Adom & Pomaa-Berko (2014) examined the impact of the automation trading system on the GSE efficiency and also reported that the Ghana equity market is still inefficient. Moreover, the rejection of the weak form efficiency and calendar anomalies are argued to be as a result of the small size of the market and considerable high transection cost which leads to inadequate market activities and less liquidity. It is worth pointing out that these arguments are only persuasive rather than empirical arguments. According to Appiah-Kusi & Menyah (2003) the market size of an equity market cannot alone lead to market inefficiency. Thus, there are no empirical possible reasons for the evidence of inefficiency and calendar anomalies on Ghana stock market in the literature.

To fill this gap in the literature, this study switches to behavioural finance to test the rationality of investors on Ghana stock market since rationality of investors is one of the cornerstones upon which market efficiency is built. According to Barberis & Thaler (2003), market agents are rational if arrival of new information is interpreted correctly and uniformly by the market participants. In addition, market participants are said to be rational if they make decisions and choices in an unbiased manner and form expectations of the future in the manner described by Baye's law (Barberis & Thaler, 2003). Overconfidence bias is used as a proxy to test the rationality of market participants on Ghana stock market. It is important emphasising that the concentration on overconfidence bias does not suggest that overconfidence is the only bias worth considering but it is due to the fact that it is reported in the literature to be one of the robust psychological widespread behavioural biases (DeBondt & Thaler, 1995). To the best of the researcher's knowledge, no study has attempted to examine the rationality of investors on GSE either by employing any behavioural biases phenomena or any other means. This study provides empirical possible reason for the observation of Ghana stock market inefficiency.

1.3 Research Objectives

The primary objective of this study is to investigate the rationality of GSE market participants by testing the existence of overconfidence behavioural bias of market actors on GSE. Overconfidence bias of investors is important since some researchers such as Akerlof & Shiller (2010) and Authers (2010) argue that overconfidence of investors is one of the major variables that trigger beliefs change of investors on financial markets and offers the necessary environment for the various market anomalies. Thus, the rationality of market participants on Ghana stock market is tested by investigating the existence of overconfidence bias on the market using data from 2000 to 2015. In view of this, the objectives of the study are:

i. To investigate whether overconfidence bias exists on GSE market.

ii. To examine whether trading volume granger cause stock returns or/and stock returns granger cause trading volume.

1.4 Research Questions

Following the objectives considered for this study which has been provided above, the following research questions are posed;

i. What is the relationship between the current GSE trading volumes and past GSE market returns?

ii. Is there a bidirectional granger-causality between trading volumes and market returns on GSE?

1.5 Significance of the Study

Assets value and quantity are considered to be the elementary pillars for market theories. Therefore, a better understanding of market participants and aggregate markets behaviour will make the understanding of financial markets easier and better. In the financial economic literature, most studies have focused extensively on understanding and explaining the linkage between assets returns, asset returns volatility and asset trading volumes. According to Karpoff (1987), the empirical nexus between asset returns and the asset trading volumes is imperative since such a relationship of empirical evidence aid a better understanding of the market information flow theories. Thus, this study provides some evidences on the relationship between equity price and trading volumes and as result gives an insight into the information flow on GSE.

The primary goal for this study is to investigate the (conditional) rationality of GSE market participants by testing the presence of overconfidence bias on Ghana stock market. This is achieved by analysing the empirical lead-lag relations existing between GSE equities trading volumes and equities returns. The evidence of current market trading volumes being explained by past equities returns is an indication of existence of overconfidence bias in the market. This study contributes to literature on behavioural finance on African stock markets in several ways. Firstly, it is one of the few studies in Africa which have considered the overconfidence behavioural bias on African stock markets. This is important because behavioural biases help in explaining some of the inefficiencies and anomalies on stock markets. To the best of the researcher’s knowledge, this is the first study that examines any behavioural bias on GSE markets. Moreover, the study contributes and expands the debate on overconfidence bias and also the causality relationship existing between asset returns and asset trading volumes by presenting evidence from Ghana. The study therefore provides an insight into rationality of GSE market participants and as a result provides empirical possible contributing reason for the inefficiency and anomalies on GSE market.

The documentation of empirical evidence of behavioural biases on financial markets is important for financial markets participants especially for hedge funds, mutual and investment funds managers in developing their trading or investment strategies. Their main aim is to diversify risk in the process of allocating their capital. If financial markets participants are rational and markets are efficient, fund managers would follow Markowitz Portfolio Theory to buy well diversified portfolios in order to balance out the expected return and expected risk. This study would provide investors the necessary knowledge in order to choose the appropriate investment strategy based on the behaviour of the market in order to maximize their investment wealth. For instance, market participants can adopt Doviak (2015) strategies for applying behavioural finance to one's practise or overconfidence bias portfolio strategy suggested by Daniel & Titman (1999) which is based on market capitalization, momentum and book-to-market ratios and reported in the literature to earn excess returns than can be explained by the traditional finance framework and Fama & French (1993) three-factor framework.

In recent times, the globalization and the interdependence of financial markets have resulted to foreign investors having keen interest in foreign markets as a way of diversifying their portfolio risk. According to Cooray & Wickremasinghe (2007), a well-researched market in terms of its efficiency and behaviour attracts foreign investment which boosts domestic savings. Therefore, this study would contribute to the research on GSE especially to the behaviour of market participants on GSE.

This study would also assist policy makers on Ghana Stock Exchange to appreciate the fact that the inefficiency on the market could be due to behavioural biases other than the argument of small market size and illiquidity of the market. The study encourages policy makers on GSE to turn to behavioural biases as the possible cause of the anomalies on the market so that the appropriate policy prescriptions such as introducing behavioural bias into the GSE programme content and caution to investors can be provided to reduce these anomalies.

1.6 Scope of the Study

Most of the empirical research works relating to behavioural biases for that matter overconfidence bias on stock markets are conducted in the developed countries using the setting pertaining there with little being documented on African markets. An empirical study in this area is highly required especially in Africa stock markets which are characterized with less liquidity, opaque and volatile. Due to constraints of access to data, this study is limited to one African stock markets namely, Ghana stock market, considering data from 2000 to 2015.

1.7 Chapter Disposition

The study is organized into five (5) main chapters. Chapter one is made up of background of the study, problem statement, research objectives and questions, significance of the study and the scope of the study as well as chapter disposition. Chapter two covers the relevant literature review on the study mainly from related journal publications in the area. Chapter three looks at the methodology or framework adopted for the study, providing relevant information on data sources, and how the data was analysed. The Chapter four of this study presents the results and discussion on the findings of the study. The Chapter five of this study presents the summary, conclusions and recommendations grounded on the empirical evidences obtained in the preceding chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The discussion of the literature review in this chapter delves into the structure of Ghana Stock Exchange, behavioural finance, investment behavioural biases, and overconfidence bias and its associated theories. Empirical literature on overconfidence bias is then reviewed.

2.2 Structure of Ghana Stock Exchange

A Governing Council made up of nine members with two representatives from listed companies, two representatives from licensed dealing members, three independent members and two executive officers steer the affairs of GSE. This Governing Council has three main committees, namely, the Listing committee, Finance committee and the Risk Management and Surveillance committee which foster the smooth running of the exchange (GSE, 2016). The prime role of the Listing Committee is to consider applications for listing whiles the Finance Committee is charged with the responsibility on financial matters of the Exchange such as budgets and remuneration (GSE, 2016). Also, the appraisal, recommendation and approval of applications for membership are the duties of the Risk Management and Surveillance committee. However, an ex-officio member is appointed as the Managing Director of the Exchange who becomes the head of the management staff and has responsibility of managing the day-to-day activities of GSE with the help of a Deputy Managing Director (GSE, 2016).

GSE is a public company limited by guarantee with its membership grouped under Associate members, Licensed Dealing Members (LDMs) and Government Securities Dealers (PDs)

(GSE, 2016). The Associate members of the Exchange are individuals and legal corporate bodies that provide the necessary support for the aims of the Exchange to be achieved. On the other hand, the LDMs are legally registered members of the exchange who are qualified to trade on the Exchange. The PDs are also legally corporate entities who have the authorization from both GSE and Bank of Ghana to deal only in securities issued by the government.

2.3 Behavioural Finance

Behavioural finance is a new and evolving paradigm of finance that studies how sociological and psychological factors of financial market participants influence market participants' decisions and choices while buying or selling assets (Nofsinger, 2001). Thus, behavioural finance focuses on the impact of psychological and sociological factors on how financial market participants make decisions and choices and its successive impacts on the markets as a whole. Behavioural finance is a multidisciplinary field of studies which employs psychological and sociological factors to explain the thinking processes of individual market participant, groups, and entities including the emotional patterns involved in their financial decision-making process. Behavioural finance tries to answer the why, how and what investors consider in their financial decisions and investing. Behavioural finance explains that psychological, social, and emotional variables like cognitive ability and neural processes as well as external environment variables such as crowd psychology and media influence are very essential to the market participants' financial decisions and the behaviour of the aggregate financial markets.

2.3.1 The Foundations of Behavioural Finance

Behavioural finance discussions in the academic literature have taken several forms and different perspectives. Numerous researchers, authors and practitioners have provided their respective viewpoints, interpretations and understanding of this new evolving field. As a result, it is necessary to explain the cornerstones of behavioural finance which are psychology, sociology and finance.

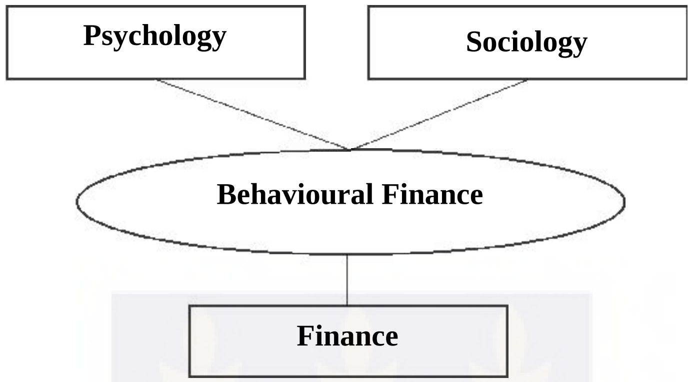


Figure 2.1: Foundations of Behavioural Finance (Source: Schindler, 2007, p. 18)

Psychology as a discipline involves the scientific study of human behaviour and their mental processes. It also considers how human mental abilities and capabilities are influenced by its physical, mental state and the outward environment. Sociology on the other hand, involves the systematic study of the social behaviour of humans and the impact of group influence on human behaviour. Therefore, the sociology aspect focuses and considers the impact of humans' social relationships on their way of life and behaviour. Finance is a discipline that primarily focuses on the determination of value and allocation of capital, including the acquiring, investing and managing resources.

Application of psychological studies in finance has revealed that economic agents persistently display certain biases in the process of forming their belief system and as a result affect their decision making. Sociology on one hand emphasizes that a lot of the financial decisions taken by market participants' result from social communication such as crowd psychology rather than these decisions being taken in isolation as postulated by standard finance theories. Thus, Sociology therefore refutes the axiom that economic agents make choices and decisions without external impacts. However, standard finance is still the linchpin in the concepts of behavioural finance but with the behavioural traits of psychological and sociological variables of humans as the primary catalyst in this new area of study. As a result, in order to appreciate behavioural finance, one must familiarize himself with the basic concept of psychology, sociology and finance disciplines in order to become acquainted with the overall theories of behavioural finance.

2.3.2 Behavioural Biases of Investment Decisions

Financial investment decisions such as where to invest one's funds, where to save and bank are routine decisions that are usually taken by several players like individual market actors, governments, institutional investors, fund managers and other players in the financial world. For example, institutional investors and fund managers have to decide which kinds of assets to hold, the percentage of funds to be allocate to the various portfolios and when to sell their positions in the markets.

One of the central goals of behavioural finance is to draw the attention and deepen the understanding of financial market players and researchers on how market agents design their expectations about the future, behave towards uncertainty and risk, make decisions and choices, what kinds of assets investors should hold and the best way to trade in the financial markets (Oslen, 2008). For such purpose to be achieved, behaviourists argue that some aspects of the standard finance axioms about economic agents must be relaxed. That is, economic agents are not as smart as standard finance theory postulates and Kahneman puts it in this way; "the mind is a system of jumps to conclusions" in his 2002 Nobel Prize Lecture. Psychological empirical evidences indicate that the economic agents' information processing ability is quite often weak. According to Newell & Simon (1972), when humans are confronted with difficult problems, they tend to rely on psychological occurrences, long memories and heuristics resulting in biases in dealing with such problems. Many studies have reported that many of these biases are as a result of analytical processing and cognitive limitations. These entire constraints limit human's capability to make accurate judgments.

According to psychologists, the human brain is a receptive of considerable large volumes of sensory signals whenever it faces a challenge that needs a solution. Psychologists claim that whenever the human brain comes into contact with a new problem, the brain recognizes the changes and as a result arranges the necessary signals in a more efficient way and in the process of doing that, a considerable amount of the data or signal is discarded instantly. Specific psychological compression system is employed by the human brain to filter the data received and as a result, only a very small proportion of it is transformed into significant information. Therefore, beliefs concerning the probability of the occurrence are then formed based upon this information, even though possible respective payoffs of the event's outcomes would be uncertain.

However, according to Kahneman, Slovic & Tversky, (1982) the determination of such probabilities and forecasting the outcome of uncertain problems are converted to simple judgmental exercise which is made possible by the human brain associating with past experiences that are stored in human's long memory. Thus, market participants usually forecast about the future and make choices when confronted with complex and uncertain problems and their choices may not be optimal since their decisions and choices are based on heuristic simplifications which lead to behavioural biases in the form of a systematic and consistent error in judgment (Chen, Kim, Nofsinger & Rui, 2007).

Behavioural biases have enormous impact on the way in which financial decision makers acquire and process information for their financial decisions and choices. However, Binmore (1999) argued that these biases can only be considered to have influential impacts on humans if it persists in an environment where persons continually come in contact with the similar decision problems. Empirical studies conducted from laboratory atmosphere to trading floors have all indicated the presence of behavioural biases when trading. Practical examples of such behaviours is what was witnessed with most market participants actively involved in trading during the 1999-2000 internet bubble and 2007 US housing burst. Table 2.1 below shows some of the major behavioural and psychological biases reported in the literature.

Table 2.1: Some of the Most Common Behavioural Biases

Ambiguity Aversion: Refers to the situation investors make preference for ambiguity-free options even when they seem less likely to succeed and rather stick with the "known" to avoid uncertainty and chaos. **Anchoring:** The tendency to hang on to previous signals such as arbitrary pricing levels when making an investment decisions. **Cognitive Dissonance:** The state of having inconsistent thoughts, beliefs and attitudes towards an investment decision. **Confirmation:** Selective screening and seeking out data to fit the existing position whilst avoiding information that undermine the positions.	**Disposition effect:** The tendency of market participants to sell winning assets and rather hold on to the ones that has fallen in value. **Optimism:** Investors believe that bad happenings occur to others; wishful thinking. **Overconfidence:** The situation where investors overestimates their own skills and abilities and also attribute failure to bad luck while success to their skills **Recency:** Overemphasis is placed upon events that are most recent.

Author's Compilation (Sources: Samuelson & Zeckhauser, 1988; Pompian & Longo, 2005)

2.4 Theoretical Review

2.4.1 Overconfidence Bias

Psychologists believe that most individuals are not well calibrated and as a result, place too much belief in the precision of their judgements and knowledge. Empirical studies in psychology on calibration of subjective probabilities indicate that individuals overestimate the correctness of their judgements and knowledge. Koriat, Lichtenstein & Fischhoff (1980) indicate that "an individual is well calibrated if, over the long run, for all answers to given questions are assigned a given probability, the proportion correct equals the probability assigned" (p. 108).

A vast number of studies have documented that people are miscalibrated in their judgements. Miscalibration is one form of overconfidence manifestation. Such overconfidence has been documented in several professional environments which include psychologists, physicians and nurses, engineers, attorneys, negotiators, entrepreneurs, managers, investment bankers, and market professionals such as security analysts and economic forecasters.

Another strand of the literature on overconfidence in psychology also shows that people are positively unrealistic in assessing themselves. According to Taylor & Brown (1988) (cited in Odean, 1998), most people perceive themselves as better than the average people and also see themselves better than others perceive them. Thus, most people perceive their skills and abilities to be greater as compared to their peers. Hence, people tend to attribute their own skills and abilities to their past positive results and therefore easily recall their successes more than their failures. Researchers argue that when people forecast the outcome of a certain event and the outcome of the event turns out to be what they forecasted, people tend to overestimate their contributions in bringing it about. Taylor & Brown (1988) (quoted in

Odean, 1998) indicated that such successive beliefs by individuals in their own abilities may result to “higher motivation, greater persistence, more effective performance and ultimately, greater success.” Researchers have documented that such beliefs can trigger biased judgements which is referred to as self-attribution bias. Several psychological evidences indicate that most individuals tend to place too much credit on their abilities and knowledge for their past success and blame external forces for their failures (Dunning, 2005).

Many factors have been identified in psychology to influence the level of overconfidence among people. Some of these factors include complexity of the task, information and base rate. Many empirical studies in the psychology literature posit that people generally exhibit overconfidence when dealing with moderate or hard difficulty tasks. Thus, overconfidence is reported to be very predominant when tasks being done are difficult and less when the tasks are easy when the difficulty level is measured by the number of people who correctly answer the question (Gigerenzer, Hoffrage & Kleinbolting, 1991). Also, the psychology literature posits that overconfidence bias is predominant in males than females.

Other studies also argue that the amounts of information people possess influence their decision-making process and as result, their confidence level. Some psychologists argue that the large amount of information influences people’s decision-making process and therefore, increases their overconfidence level. However, in an experiment conducted by Peterson & Pitz (1986), using baseball wins prediction, revealed that large amounts of information to people rather decrease overconfidence level since it increases the level of accuracy. Thus, there is a mixed result in the psychology literature as to whether large amounts of information increases overconfidence bias.

Also, research has shown that the rate at which people assess their own decisions or behaviour to some extents depends on what majority of the people perceive as norms of the community or group the people belong to. Comparing one's belief or decisions with the larger community or group's believes that an individual is a member of shows whether the individual is consistent or inconsistent with the common norm. Consistency of an individual's decisions or beliefs with the larger group increases the individual's overconfidence level because being consistent with the community norm seems to confirm one's confidence. The behaviour of an individual with regard to that of the population expressed as a percentage is called base rate in the psychology literature.

2.4.2 Overconfidence Bias in financial markets

Black (1986) indicated that irrational noise market participant's beat the trading equilibrium postulates by standard finance theory. Black (1986) also argued that the expectations of noise traders deepen the challenge of forming models on the workings and behaviour of financial markets. Also, De Long, Shleifer, Summers & Waldmann (1990) also posits that market participants employ their beliefs of future cash flows of a security when selecting their securities and portfolios but not the risk associated with such returns. De Long et al. (1990) further argued that rational market participants must not compete with irrational or noise market participants since it's risky and costly. As a result, many researchers using noise traders' characteristics have developed models and empirical tested such models and prominent among these characteristics is the overconfidence bias.

Overconfidence bias is cognitive psychology bias which is adopted into finance to help explain how decisions of market participants are biased. Overconfidence bias occurs where market agents' confidence judgements are reliably stronger and greater than the correctness of those judgements. Overconfidence relates to economic agents who are too confident and exaggerate their own skills and capabilities in dealing with problems (Nofsinger, 2001). Overconfidence bias is the phenomena observed when economic agents think, believe and behave as if they are smarter and poses superior market information than what they actually possess. Daniel & Hirshleifer (2015) state that "Overconfidence means having mistaken valuations and believing in them too strongly" (p. 61). Overconfidence is the propensity of economic agents to put unwarranted level of confidence in their skills and abilities (Grinblatt & Keloharju, 2001).

It is reported in both the psychology and finance literature that overconfidence bias is the most robust empirical cognitive bias with its evidence cutting across several professions. DeBont & Thaler (1995) indicated that "perhaps the most robust finding in the psychology of judgement is that people are overconfident." The argument that overconfidence bias is one of the most robust finding is also confirmed by Shiller (2000) who also state that "yet some basic tendency towards overconfidence appears to be a robust human character trait: the bias is definitely toward overconfidence rather than underconfidence" (p. 142). Overconfidence bias has been observed among financial practitioners. For instance, Ben-David, Graham & Harvey (2013) documented overconfidence bias among corporate financial officers whiles Glaser, Langer & Weber (2013) also documented overconfidence bias among investment bankers and professional traders.

One of the remarkable questions to ask is why might financial researchers expect market participants in financial market to exhibit overconfidence? The primary answer for this question is that overconfidence is a widespread psychological occurrence and is characterised by a cluster of related effects. A trader in financial market's basic aim is to select securities that would provide him superior returns in future than other securities, which is a complex activity but it is in this activity most traders depict the overconfidence characteristics. Nofsinger (2001) states that "overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Does overconfidence occur in investment decision making? Security selection is a difficult task. It is precisely this type of task at which people exhibit the greatest overconfidence." (Nofsinger, 2001, p. 138)

Predictability of an event which has low probability of occurrence such as securities returns is documented to be the tasks that market participants have the highest tendency to be overconfident since experts tend to overweight their models and theories. The psychology literature demonstrates that overconfidence is more prone in activities which require judgment such as making diagnosis of sickness and tasks characterised with delayed feedback such as predicting a market returns as against activities that offer immediate and conclusive outcome feedback and mathematical tasks such as solving calculation problems (Griffin & Tversky, 1992).

2.4.2.1 Overconfidence bias theories in finance

Financial economists over the years have been puzzled over the eagerness of economic agents to be involved in active trading in financial securities which is regarded to be highly competitive. Empirical studies have shown that overconfidence in market participants' security analysis skills is a widespread and persistent behavioural phenomenon and as a result financial economists have postulates theories on overconfidence bias in financial markets. Overconfidence theories in the finance literature are still evolving. Researchers in finance have developed overconfidence theories and provided testable implications under two main perspectives.

Odean (1998) postulates overconfidence of market participants as overestimation of their information precision. Odean (1998) explains that overconfident market participants overestimate the accuracy of their information and behave to have useful signals when in fact they have no useful information. The researcher further explains that overconfident traders can trigger markets underrection to information resulting to positive serially correlated returns when they underweight new information and also cause markets overreaction leading to negatively serially correlated returns when they overweight new information. Odean (1998) explains that the level of this underreaction or overreaction effects on the markets depends on the proportion of all market participants who underweight or overweight their information. However, the researcher did not distinguish between public signals and private information signals.

As a result, Daniel, Hireshleifer & Subrahmanyam (1998) presented overconfidence bias theory which explains overconfidence as overestimation by market participants as to the precision of their private information than the public available information. In the world of finance, financial analysts and other market participants gather information which they believe to be relevant for their trading activities through various avenues like rumours and analyses of financial statements. According to Daniel et al. (1998), when an analyst places much weight on his ability and skills to gather information, the analysts tend to undercut their forecast error. Therefore, the analyst becomes overconfident about signals that he has come up with and not the public available information. Daniel et al. (1998) argues that when market participants receive confirming private signals, their overconfidence level increases but receivable of disconfirming private signals trigger their overconfidence level to decrease. Accordingly, they define overconfident investors "as one who overestimates the precision of his private information signals, but not of information signals publicly received by all" (Daniel et al., 1998, p.1841). Researchers have shown that varying abilities of traders for selecting stocks might arise from overweighting of their private signals than the signals available for the general public. This theory postulates that stock prices on competitive securities markets overreact to private information signals and underreact to public signals. Therefore, several empirical studies by researchers have modelled investors' overconfidence as an overestimation of the precision of their private information (such studies include Hirshleifer & Luo, 2001; and Scheinkman & Xiong, 2003).

Another theory of overconfidence bias in the finance literature is built on the self-attribution bias psychology theory. Psychologists have empirically demonstrated that people tend to attribute past success to their abilities and failures to external variables (Hastorf, Schneider & Polifka, 1970 (cited in Gervais & Odean, 2001)). In the financial market context, self-attribution bias leads to overconfidence bias when successful investors ascribe their past success to their own skills and abilities of selecting securities and failures to bad luck. This implies that overconfidence bias resulting from self-attribution is a dynamic phenomenon since past outcomes of investors keep on changing overtime. Hirshleifer (2001, p. 1549) states that "Overconfidence and biased self-attribution are static and dynamic counterparts."

Gervais & Odean (2001) used the self-attribution psychological bias theory to develop a theory that investors infer their ability from their past successes and failures which lead them to become overconfident. The researchers postulate that when market participants become successful in their trades, they tend to attribute too much credit to their own skills and as a result upgrade their beliefs about their abilities upwards which trigger market participants' overconfidence. Thus, the theory assumes overconfidence is a dynamic phenomenon which changes with investors' successes and failures. As a result, the researcher argue that market participants who have been trading in the market for a short period are characterised by greater overconfidence compared to more experience market actors who have developed better self-assessments. Gervais & Odean (2001) further argue that overconfidence bias of investors resulting from their past positive trading returns causes investors to trade more in subsequent periods. Also, several empirical studies have modelled investors' overconfidence as resulting from past market performance leading to excessive trading (such studies include Statman, Thorley & Vorkink, 2006; and Chuang & Lee, 2006).

2.4.2.2 Implications of Overconfidence bias on financial markets

The theoretical explanations of overconfidence bias as discussed above have been documented in the literature to have various implications on financial markets around the globe. It is important indicating that most of these implications have been tested by researchers on different markets.

2.4.2.2.1 Overconfidence bias and Trading Volume

Researchers over the years have argued that information is gradually introduced to the security market through market participants trading (Benos, 1998). However, past studies do not specify the kind of information impeded in trading volume as well as the content and source of the information. As a result, a number of recent empirical studies postulate that overconfidence of traders trigger the excessive trading volumes witnessed in the global financial markets (Odean, 1998; Daniel et al., 1998; Gervais & Odean, 2001; Statman et al., 2006). These studies explain that the relationship between overconfidence bias and trading volume exists predominately in the market since market participants who tend to be overconfident overestimate their own security selecting, signals and valuation skills. As a result, trade more on the average than the rational market participants. It was argued that overconfidence arises from traders' overestimation of their private information and as a result triggers traders to hold different beliefs which also lead to overestimation of their belief systems. Therefore, it is argued that strong opposing belief systems strongly held in the markets are necessary and sufficient grounds for high trading volumes to be witnessed.

Overconfidence of market players is reported in the literature to explain excessive trading volumes being observed on financial markets. DeBont & Thaler (1995) note that "the key behavioral factor needed to understand the trading puzzle is overconfidence" (p. 393). Thus, investors who exhibit overconfidence characteristics usually end up doing too much trading. According to Shiller (2000), "overconfidence, however generated, appears to be a fundamental factor promoting the high volume of trade we observe in speculative markets" (Shiller, 2000, p. 144). It is reported that overconfident market actor trade excessively in such a way that their transection cost surpasses their expected gains. The concept that overconfidence bias of market participants causes them to trade excessively is tested by many studies such as Statman et al. (2006) and Chuang & Lee (2006). These studies confirmed the assertion that overconfident invertors trade too much.

2.4.2.2.2 Overconfidence bias and Market returns

Overconfidence bias and market return nexus has been documented in the behavioural finance literature. In the literature, it is argued that market returns have an impact on the level of investors' overconfidence. Thus, investors draw their level of confidence from past market results.

According Gervias & Odean (2001), market participants who make profitable trades tend to be more overconfident due to the better than average overconfidence resulting from self-attribution bias. As a result, they developed a model to assess how market participants learn about their abilities. They indicated that the overconfidence level of market participants changes and can be attributed to their previous success and failure. For instance, in a bull market, market actors easily make gains and as a result, tend to be more overconfident. They associate the success to their own expertise ignoring the fact that the gains they are enjoying are total market phenomena at that point in time. More specifically, the literature explains that aggregate overconfidence is higher if market returns are positive. In the same way, the overconfidence level decreases during a negative market returns as investors blame external factors for their failure.

According to Glaser & Weber (2009), both previous market returns and also previous portfolio returns have significant impacts on an investor’s behaviour but the past market returns has superior impact on market participants overconfidence. Also, Statman et al. (2006) and Chuang & Lee (2006) indicate that past market returns have strong and significant impact on market participants’ overconfidence.

Daniel & Hirshleifer (2015) argued that overconfidence plays a vital role of understanding return anomalies observed on financial markets which are normally attributed to market participant’s limited attention. They claim that the assertion of limited market participants’ attention has enormous impacts on price if the market participants are overconfident and as a matter of fact do not realise that the importance of the information they are neglecting.

2.4.2.2.3 Overconfidence and differential reactions to private and public information

Overconfidence bias theory such as Daniel et al. (1998) postulates that overconfident market participants overreact to their private information whiles underreacting to public available information. Daniel et al. (1998) argues that overconfident investors place more weight on their private information and as a result overreact to arrival of private information signals. On the other hand, market participants place less weight on public information and as a result underreact to public information. Therefore, it is argued that a shock of private and public information drives stock returns and trading volume. Thus, researchers postulate that overconfident investors put too much weight on their private signals which causes stock price to overreact.

One strand of the literature explains that private information plays more significant role in driving trading volume than public signals (Liorente, Michaely, Saar & Wang, 2002). On the other hand, some researchers explain that market participants' various interpretations and analysis of public signals rather trigger trading volumes. However, the overconfidence theory posits that overconfidence market participants overweight the precision of their private information and underweight public signals and a result trade excessively (Odean, 1998; Daniel et al., 1998). Chuang & Lee (2006) tested this overconfidence implication and confirmed its validity.

2.4.2.2.4 Overconfidence bias and excessive volatility

Quite a number of empirical studies have documented that volatility of stock prices are more volatile than an efficient market theory postulates (such studies includes Shiller, 1981). One of the common explanations given to this puzzle is the habit formation model. The habit formation model explains that investors' consumption variations relative to their habit lead to variation in the risk aversion of investors and therefore leads to changes in price-to-dividend ratios. This changes aid to decrease the gap between the dividend growth volatility and returns volatility.

However, overconfidence bias is suggested as an important contributing factor responsible for the excessive volatility observed on financial markets. For instance, Chuang & Lee (2006) formulated a model to test whether excessive trading of overconfidence market participants contribute to the documented excessive volatility. They reported that overconfident market participants' excessive trading behaviour contributes to the documented excessive volatility. It is worth pointing out that, the overconfidence literature does not argue that overconfident market participants excessive trading is the only source of excessive volatility observed on financial markets.

2.4.2.2.5 Causality relations between trading volume and stock returns

The causal relationship between trading volume and stock returns have been documented in the literature to explain several phenomena on financial markets. Hiemstra & Jones (1994) postulate that stock returns and trading volume causal relationship provides an insight into changes in stock prices in relation to movements in trading volume. In the literature, it is argued that past trading volume cannot trigger current securities price in an efficient market. However, causality running form securities prices to current trading volume is explained as market participants basing on past securities prices behaviour to predict the future prices behaviour of the securities (Brennan & Cao, 1997). The causality relation between trading volume and returns have received much attention in recent times and Chen, Firth & Rui (2001) state that "the important issue should be whether information about trading is useful in improving forecasts of price changes and return volatility" (p. 155).

Moreover, other explanation to the price – causality is the sequential arrival information hypothesis postulated by Copeland (1976) and Jennings et al. (1981) later extended it. The sequential arrival information theory suggests a positive bidirectional causal relationship between absolute values of price changes and trading volume. Sequential arrival information framework assumes that the release of new information into the market is not disseminated to all market agents simultaneously but the new information is release to one agent at a time. As a result, the final information equilibrium is reached only after sequences of transitional equilibriums have been achieved. Consequently, lagged absolute returns may trigger current trading volume and vice versa due to sequential flow of information. For instance, Hiemstra & Jones (1994) claimed that sequential information flow leads to lagged trading volume to trigger current absolute price changes and lagged absolute price changes having predictive power for current volume.

Lakonishok & Smidth (1989) also demonstrated that current volume can have relation to past stock price changes due to tax – and non – tax associated trading motivations. For that reason the causal relation for tax – associated trading motivations is negative whiles non – tax associated trading motivations are positive.

Furthermore, the price and volume causality relationship can be explained by the noise – trader model proposed by De Long et al. (1990). The noise – trader model argues that the market activities of noise traders which deviate from the basic economic fundamentals usually leads to stock prices mispricing in the short run. According to De Long et al. (1990), in the absence of transitory component, the price moves to its mean value in the long run. Thus, in the noise trader model, positive causal nexus running from stock returns to trading volume follows the positive feedback trading strategy of noise traders who usually rely on past price changes to make their decisions.

Statman et al. (2006) argues that little past empirical studies have considered current volume and lagged returns relationship in the literature. They further argue that these empirical findings fail to recognize that overconfidence bias of market participants may also be the reason for causality running from past returns to current volume. One of the implications of overconfidence hypothesis is the relation between current trading volume and past stock returns. A causality running from lagged market returns to current trading volume is explained to be an evidence of overconfidence bias. Researchers argue that market participants draw their source of overconfidence from previous market returns and as a result trade more in subsequent periods. This argument is consistent with Daniel et al. (1998) and Gervais & Odean (2001) overconfidence hypothesis that overconfidence is keenly promoted in a bull market. Based on this argument, Chuang & Lee (2006) developed a bivariate Granger causality tests framework to differentiate between the overconfidence bias and other trading volume hypothesis. Based on their model, they concluded that granger-causality running from lagged market returns to current trading volume is an implication of overconfidence bias on financial markets.

2.5 Review of Previous Studies on Overconfidence bias in financial markets

Behavioural finance and for that matter overconfidence bias in finance is a new area emerging in the literature and for that matter not much empirical evidences have been documented on overconfidence bias. However, there are some evidences of overconfidence bias from both advanced and developing markets.

2.5.1 Evidence from Developed Markets

Odean (1998) argued that market participants are overconfident and that overconfidence bias affects financial markets activities. The study indicated that the how is dependent on which individuals are overconfident in the market and moreover how information in the market is disseminated. The study examined markets where the market agents are price-taking traders, a strategic-trading insider and risk-averse traders. As a result, the study employed three different kinds of empirical models to achieve this multidimensional analysis of overconfidence.

Based on the results of the analysis, Odean (1998) argued that when market participants are price takers, insiders or market makers then their overconfidence would result to increase in trading volumes. The study claimed that this finding is the most robust empirical evidence of effect of market participants' overconfidence. Thus, when overconfidence of price takers increases, price takers measure their own signals greatly than they weight those of other price takers in the process of forming their beliefs. Therefore, their subsequent beliefs become more dispersed and a matter of fact more trading takes place. Also, when an insider investor becomes overconfident, the insider investor believes and places more weight on the private information in his possession and has more precision than the reality is and forms a posterior expectation farther from optimal which leads the insider to trade more aggressively leading to increase in expected volume. Odean (1998) indicated that overconfident market markers usually have flatter supply curve and this motivates market makers who are price sensitive to trade more. This implies that, with all the three settings of market participants, overconfidence bias of market participants result in high volumes of financial securities being traded.

Empirically, Odean (1998) revealed that overconfident market participants can trigger markets underreaction to information which would lead to returns of the market being positive correlated. On the other hand, overconfident market participants can cause market to overreact to information which basically leads to negative serially correlated returns. Furthermore, the study argued that the level of the under reaction or over reaction rests on the proportion of market participants who actually underestimate or overestimate their own information. However, this result is consistent with the concept in the psychology literature that individuals underestimate the difficulty when dealing with highly statistical and abstract information and rather places more weight on salient and extreme information.

Odean (1998) empirically proved that traders expected utility reduces as a result of overconfidence. For instance, in the world of price taking traders, there are no exploitation because there is the absence of noise traders and hence the total market returns expected from the market activities must be zero. The study argued that in settings where overconfidence arises from traders' overestimation of their private information triggers traders to hold differing beliefs which also result in overestimation of their belief systems. Therefore, the study argued that strong opposing belief systems strongly held in the markets are necessary and sufficient grounds for high trading volumes to be witnessed, high returns volatility in the market to occur, deviation from intrinsic securities prices to be witnessed and reduction of participants expected utility. Thus, overconfidence of market participants would reduce their expected utilities since it leads to non-optimal risk sharing and as a result overconfident market actors are in a position to hold not well diversified portfolios.

The study further reported that overconfidence causes market depth to increase. Also, insider traders who are overconfident improve financial assets quality price whereas overconfident investors who are price takers worsen it. The study also revealed that overconfidence has an effect on volatility and this is also dependent on who is overconfident. This study actually prepared the grounds for much more empirical studies on overconfidence to be conducted and provided several testable implications of overconfidence.

Daniel et al. (1998) argued that some empirical studies reported in the literature indicate that markets underreact to information whiles others report overreaction evidence but there was no theory in the literature to incorporate these empirical evidences and further make suggestions as to when market overreaction or underreaction would occur. Therefore, Daniel et al. (1998) fill this gap in the literature by postulating that overconfidence of market participants result from market participants' overreaction to private information while underreacting to available publicly information.

Their theory was founded on the grounds that a significant amount of errors made by market participants is their misinterpretation of their own new private information. In their results, they indicated that informed traders who are overconfident end up losing money. Furthermore, the study reported that overconfidence of risk-averse traders with regards to genuine information permits them to make most use of the information and as a result their expected returns can exceed that of fully rational traders.

With their model having its foundation on traders' overconfidence bias resulting from traders becoming more confident about their private information, Daniel et al. (1998) argued that the predictability of returns would be highly great and consistent for securities having the greatest information asymmetries. Daniel et al. (1998) further demonstrated that the presence of investors' overconfidence in the markets may be the reason for the observed negative long-lag returns autocorrelations and excessive volatility observed in some financial markets. Daniel et al. (1998) study provided breaking grounds for more studies on overconfidence bias in finance to thrive on.

Odean (1999) argued that since there is no model that establishes the required and good level of trading volume to be observed in financial markets, it becomes extremely challenging to investigate whether trading volumes observed in financial markets are too high. The study then argued that if aggregate market trading volume is high, then the trading volumes of some group of market participants must be high. Therefore, the study employs discount brokerage accounts class of investors and postulates that due to the overconfidence of the discount brokerage investors, they trade too much. The study indicated that the use of discount brokerage investors trading activities is very good for investigating overconfidence bias of excessive trading since the discount brokerage is not characterised by complicated agency problems.

Odean (1999) reported that some of the market participants trade too much in such a way that on the average their overall trade gains are reduced. The study demonstrated that after excluding market activities that may have been inspired by investors' demands for liquidity, tax loss selling, rebalancing of portfolio or changing to securities with lower risk, too much trading still reduces returns. The findings of the study also revealed that overconfident investors even trade more when the cost of trading is ignored and this actually reduces their profits and as a result even claim that this empirical finding is more extreme compared with what overconfidence theory predicts.

Similarly, the study investigated the return behaviour of these investors before and after they have made a security purchase or sale. Odean (1999) indicated that most of these investors purchase financial securities that over the past six or more months have decreased or increased in value. Also, the study reported that, on the average, these investors tend to sell financial securities that have increased swiftly in recent weeks and claim that these observed patterns are not easy to comprehend. The study suggested that the possible reasons for these observed patterns may be due to the large number of financial assets available for investors' choices or the influence of external sources such as financial media or may be due to the disposition effect of the investors.

In addition, Barber & Odean (2001) indicated that psychological research has demonstrated that men have the higher tendency to be overconfident compared to women especially in male-dominated areas like finance. It is also documented in finance literature that investors who exhibit overconfidence usually overestimate the precision of their private information and as a result trade excessively. Inferring from these two statements, Barber & Odean (2001) investigate the hypothesis that men are more overconfident compared to women and as a result trade more and perform worse compared to women. In order to achieve this purpose, they employed 35,000 households' data on both men and women on their investment behaviour towards common stocks from a large discount brokerage firm which spans from 1991 to 1997.

The results of the study provided a strong empirical evidence for the hypothesis that men truly trade more compared to women and as a result decrease men returns more as compared to women returns decrease. They indicated that these empirical evidences are more robust and more evident between single men and women. They reported that on the average men tend to trade approximately 45% more than women and this behaviour results in decrease of men's net returns by approximately 2.7% annually compared to 1.7% for women. Barber & Odean (2001) therefore concluded that overconfidence among men is higher than among women.

Gervais & Odean (2001) also developed a multi-period market model which describes both the steps and channel through which market participants get to know about their abilities and how a bias in such instances lead to overconfidence. In their model, market participants are assumed firstly to not be aware of their own trading abilities and that market participants deduce their abilities from their previous trading successes and failures. That is, in the process of market participants assessing their abilities and competence level, they end up placing more credit of their successes to their own skills and as result becomes overconfident. Gervais & Odean (2001) argue that investors' overconfidence is a dynamic phenomenon and therefore changes with trading successes and failures of traders. The study indicated overconfidence bias is more evident in traders' learning stages of their trading profession and as traders mature in their career they develop a better assessment of their own abilities. One of their major hypotheses was that they expect aggregate overconfidence to be higher whenever the market experience gains, and lower after market losses. Therefore, greater overconfidence results in greater trading volumes and market losses leads to lower trading volume.

Gervais & Odean (2001) further argued that since traders become overconfident based on their successes, overconfidence does not lead to traders becoming wealthy but rather the processes involved in becoming wealthy make traders overconfident. Basing on their wealth, traders who exhibit overconfidence bias are not in danger of exiting from the marketplace, however, as they become more experienced the trader's level of wealth and confidence diminishes. They further indicated that in a market where inexperienced market participants are born always into the market and the experienced ones fade out, overconfidence would persist in the markets and therefore overconfidence market participants can play a significant part in the behaviour of the global financial markets.

The findings of the study indicated that most investors tend to take too much credit for their own successes which leads to overconfidence. The results also reported that overconfident traders trade too aggressively which leads to excessive trading volumes. The study revealed that traders' level of learning bias increases the trading volume and returns volatility observed in financial markets. The study empirically documented that overconfident traders exhibit suboptimal behaviour in their trading and as a result lowering expected future gains. Put differently, a more experienced and successful market participant has lower expected returns compared to a less successful trader. The study also showed that a high level of overconfidence triggers greater trading volumes and that trading volume would be greater after market gains. However, it is worth pointing out that unlike De Long, Shleifer, Summers & Waldmann (1991) model in which bias traders survive by locking in greater profits, Gervais & Odean (2001) model postulate a market in which the overconfident trader earns on average lower profits.

Biais, Hilton, Mazurier & Pouget (2005) experimentally investigated the impacts of psychological factors on market participants' financial behaviour by focusing on miscalibration and self-monitoring. Biais et al. (2005) explained that miscalibration as a form of judgemental overconfidence resulting from participants placing more weight on the precision of their information and self-monitoring as a form of investors' attentiveness to its environment. Employing questionnaires and 245 respondents, they investigate these two factors by studying the behaviour of these respondents under experimental financial market settings. The study postulated two hypotheses. Firstly, Biais et al. (2005) anticipated miscalibrated traders to underestimate the uncertainty of securities price in such a way that they are exposed to the winner's curse. Secondly, Biais et al. (2005) anticipated high self-monitors to act tactically and achieve superior results.

The study reported that miscalibration judgemental overconfidence leads to low trading performance and as a result investors' overconfidence results to lower gains. On the other hand, the study indicated that self-monitoring enhances trading results and high self-monitors have high probability of escaping from the winners' curse trap. Therefore, it is possible to make an inference that this experimental market study employed the winner's curse traps to be the channel through which the impacts of miscalibration and self-monitoring can be measured.

Consistent with the findings of Barber & Odean (2001), Biais et al. (2005) also reported that men tend to trade more compared to women. However, while Barber & Odean (2001) employ gender as proxy for overconfidence, they reported that there exists no correlation between miscalibration judgemental overconfidence and gender. However, their results also revealed that miscalibration overconfidence in men worsen their trading performance while it does not influence the trading performance of women.

Statman et al. (2006) argued that recently investors overconfidence theories such as Gervias & Odean (2001) paper provides the basic framework that calls for an empirical investigation to ascertain the validity of their claim that some market participants become more overconfident resulting from observed positive portfolio returns and exhibit low level of overconfidence following negative portfolio returns by employing both market-wide and security-specific data. The study employed from 1962 to 2002 monthly observations time series data on all NYSE/AMEX common stocks. Statman et al. (2006) adopted VAR model and its associated impulse response functions to investigate the lead-lag relationship between turnover and market returns.

One of their major findings is that, there exists a statistically significant evidence for market-wide trading volume (used turnover as proxy for trading volume) to upsurge in periods following high positive market returns after introducing volatility and portfolio rebalancing as control variables. Statman et al. (2006) claim that the market-wide evidence documented can also be attributed to the manifestation of disposition effect of investors. Therefore, in order to substantiate their claim, they employ this VAR and impulse function models to individual stocks with the intention of empirically differentiating between overconfidence bias and disposition effect. The study also reported that a security turnover is significantly explained by previous market returns after the introduction of previous security returns and indicted this evidence buttresses the overconfidence bias hypothesis. However, Statman et al. (2006) stated that their empirical evidence is more prominent in small-cap stocks.

The findings of the study indicated a lead-lag nexus between market-wide turnover and market-wide returns which confirms Gervais & Odean (2001) theory on investors' overconfidence. This finding indicates the economic importance of high positive or negative returns on subsequent market trading volume as well as the behaviour of the market. Statman et al. (2006) interpreted this lead-lag relationship as empirical evidence of overconfidence bias hypothesis. Consistent with the financial economics literature, the study also documented a contemporaneous positive nexus between trading volume and returns volatility. It is important to say this study provided the methodological grounds for many studies on overconfidence bias to be conducted.

Chuang & Lee (2006) also conducted a study on the empirical implications of overconfidence bias hypothesis. In the study, the authors formulated four main empirical frameworks in an attempt to provide empirical evidences of the validity of the overconfidence hypothesis as reported in the literature with specific attention to an aggregate behaviour of overconfident investors. Firstly, Chuang & Lee (2006) hypothesize that investors who exhibit overconfidence bias tend to overreact to their own private information and underreact to public available for all information. Also, overconfidence bias of investors arising from high past market returns triggers more aggressive trade by these overconfidence investors in subsequent periods. Thirdly, Chuang & Lee (2006) examine whether overconfidence bias of investors has significant effects on the observed market dynamic volatility. Lastly, they hypothesize investors overconfidence would lead investors to underestimate risk and as a result trade more in financial assets that are riskier.

In order to examine the shock of private and public information on securities prices, Chuang & Lee (2006) employed a restricted bivariate moving average representation model. They claim that “with an initial underreaction, stock prices overreact to private information followed by a correction process, and underreact to public information reaching an equilibrium response without a significant long-run reversal” (Chuang & Lee, 2006, p. 2503). This evidence they documented provides an empirical support for their first framework of overreaction to private information and underreaction to public information by overconfident investors. This evidence they documented also confirms the overconfidence bias arguments of Daniel et al. (1998).

In order to investigate the dynamic relationship between stock returns and trading volume as postulated by Gervais & Odean (2001) hypothesis, they employed granger causality tests if causality runs from market returns to trading volume. The results of the study indicated that there exists a significant causality running from returns to trading volume. This implies that low (high) market returns of securities granger cause low (high) trading volume in the market. They also indicated that this positive dynamic nexus documented between returns and trading volume is robust even for sub-sample periods.

With respect to investors asymmetric trading behaviour the study provided the evidence that in a bull market, investors trade more aggressively compared to a bear market. Employing GARCH-type specifications, they concluded that market participants become overconfident and as a result excessively trade. It is worth pointing out that this empirical finding provides evidence to support Gervais & Odean (2001) overconfidence hypothesis.

In order to ascertain the validity of the claim that overconfidence investors' excessive trading contributes to the documented high market volatility, they decomposed the market trading volume into two components. Firstly, the overconfidence component which is trading volume relating to past returns and non-overconfidence components which is trading volume unrelated to past returns. Chuang & Lee (2006) then examine the nexus between these two components and volatility of stock returns. They found that the overconfidence component positively accounted for conditional volatility and concluded that this finding is empirical evidence supporting the hypothesis that overconfidence market participants' excessive trading contributes to observed excessive volatility in the financial market.

Also, in order to test the validity of the hypothesis that overconfident market participants underestimate their risk and trade more in riskier assets, using firm-specific risk and return volatility as proxy for risk, they formulate two portfolios which are based on the degree of each risk. The study then employs seemingly unrelated regression (SUR) to test this hypothesis. The findings of the study indicated that stocks with higher risk had strong high-volume impact which confirms the hypothesis that if market participants are overconfident, they deal in riskier financial assets.

Overall, this study makes available intensive and extensive empirical evidences for the manifestations of overconfidence bias in financial markets. This study has provided one of the comprehensive empirical evidences of the numerous extrapolations of the overconfidence bias hypothesis and demonstrated that the overconfidence hypothesis remains one of the best possible viable explanations of many observed anomalous in financial markets.

2.5.2 Evidence from Emerging Markets

Zaiane & Abaoub (2009) following the work of Statman et al. (2006), they investigated the presence of overconfidence bias in the Tunisian market employing the VAR model. However, Zaiane & Abaoub (2009) found evidence for the overconfidence hypothesis but indicated it is remarkably weak. That is, previous market returns influence current trading activities of market participants in subsequent months. That is, the paper provides empirical evidence from the Tunisian stock market on overconfidence bias of market participants' impacts on trading volume. Also, consistent with the literature, Zaiane & Abaoub (2009) reported contemporaneous positive nexus between trading volume and returns volatility.

Muhammad & Khalid (2012) also tested two implications of overconfidence bias in Pakistan. Thus, the study examined the nexus between overconfidence and trading volume as well as overconfidence and volatility on Karachi Stock Exchange, Pakistan. With respect to the nexus between trading volume and overconfidence bias, Muhammad & Khalid (2012) followed Statman et al. (2006) paper; and with respect to trading volume and returns volatility, Muhammad & Khalid (2012) also followed Chuang & Lee (2006) paper. Consistent with Statman et al. (2006) overconfidence hypothesis predictions, Muhammad & Khalid (2012) report a significant evidence of past market returns relationship with current trading volume after controlling for returns dispersion and returns volatility. However, Muhammad & Khalid (2012) indicated that there is no significant positive contribution of overconfidence to conditional returns volatility.

Metwally & Darwish (2015) employing monthly data from 2002 to 2012 also investigated the evidence of overconfidence bias on Egypt stock markets by following Statman et al. (2006). Metwally & Darwish (2015) also report a significant empirical evidence of the impacts of past market returns on current trading volume (used turnover as proxy). Based on this finding, they concluded that there is an empirical evidence of investors' overconfidence bias on Egypt stock market. Metwally & Darwish (2015) also indicated that the market states at a particular point in time are strong and significantly affect the trading activities on the Egyptian stock market especially in a bull market.

CHAPTER THREE

RESEARCH METHODOLOGY

2.1 Introduction

In the preceding chapter, a comprehensive review of existing theory and the literature on overconfidence was presented. This served as a guide to the researcher on the choice of the estimation techniques to be employed in analysing the data. Explaining the methodology for the study is the focus of this chapter. In this chapter, data sources, variables used in the study, and empirical methodologies used for this study are discussed.

3.2 Data Sources

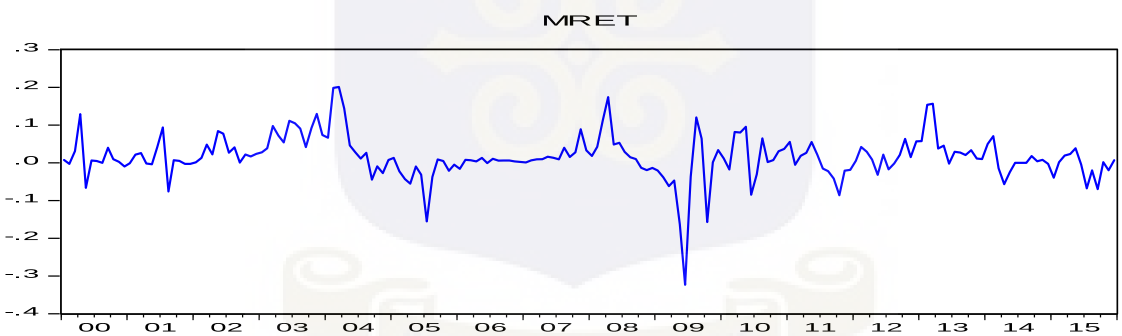
In order to achieve the objectives of this study, secondary data (monthly GSE-index value, monthly trading volume, monthly consumer price index and 91-days treasury bill rate) was obtained from the Ghana Stock Exchange and the Bank of Ghana for the analysis. The GSE – index value and trading volume was obtained from Ghana Stock Exchange database and the macroeconomic variables were also obtained from the Bank of Ghana (BOG) time series database.

The data used for the analysis is monthly based observations, specifically within month daily GSE – index value data is used to compute the monthly volatility. Approximately 3,440 daily index observations of GSE – index value and 192 monthly observations for all the variables are used for this study.

3.3 Sample period

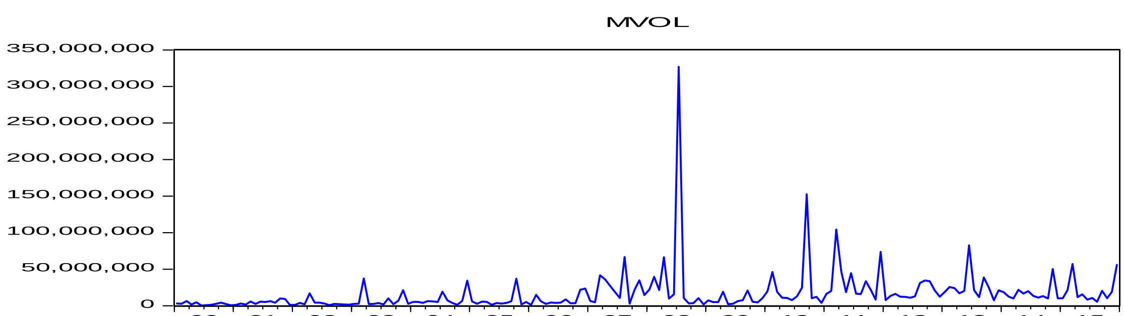
The operation of GSE began from 1990 but this study focuses on a sample period spanning from January, 2000 to December, 2015 as a result of the inability of the researcher to obtain the needed data on trading volumes for the early periods. In order to achieve reliable results, the sample period from 2000 to 2015 and sub-sample financial crisis period (January, 2008 to December, 2010) were considered. The financial crisis sub-sample period were considered due to the volatility clusters (See Figure 3.1 and Figure 3.2) that manifests in monthly GSE – index returns ($MRET$) and monthly trading volume ($MVOL$) which may be due to the 2008 global financial crises. Thus, in order to remove the possible impacts of the 2008 global financial crises from the model, a dummy variable, $dum08$ that takes 1 for January, 2008 to December, 2010 (otherwise, 0) is introduced.

Figure 3.1: A Graph of GSE-index Monthly Returns (MRET) on GSE from 2000 – 2015



Source: Author’s own computation based on data from GSE database from 2000 – 2015

Figure 3.2: A Graph of Monthly Trading Volumes (MVOL) on GSE from 2000 – 2015



Source: Author’s own computation based on data from GSE database from 2000 – 2015

3.4 Market Activities of Ghana Stock Exchange from 2000 – 2015

The GSE started operations with 11 listed companies and with three brokerage firms. Over the years, many companies have been listed on the exchange even though the number of listed companies is still recognized to be small with regards to other African equity markets such as Nigeria, Kenya, Egypt, Morocco and South Africa. The size of listed equities on the exchange grew from 11 to 29 listed equities as at 2009; 35 equities in 2012 were listed; and as at December 2015, 38 equities were listed on the exchange. Listed companies are from the financial sector, distribution sector, the food and beverage sector, ICT, insurance sector, agriculture, education, manufacturing and mining sectors of the economy.

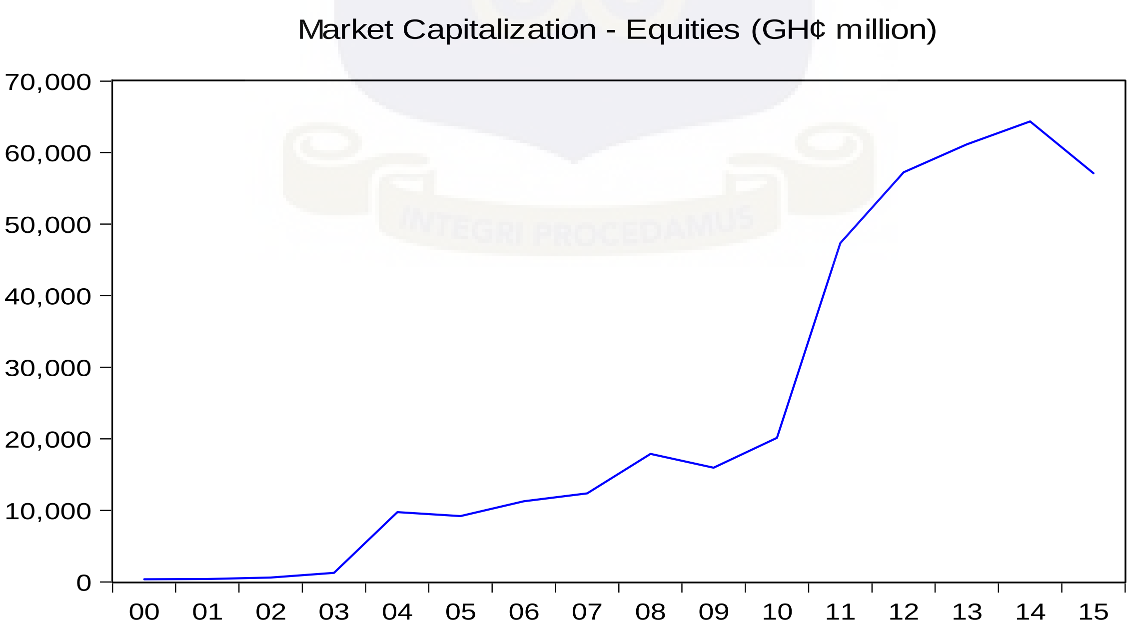
From its inception in 1990, GSE had only three (3) Licenced Dealing Members but as at the end of 2015, the GSE could boast of twenty-one (21) Licensed Dealing Members. It is worth pointing out that GSE operate on fully automation trading platform. GSE market opens each working day from Monday to Friday with official market activities taking place from 10:00am to 15:00pm except holidays pronounced by the authorities of the exchange in advance. The types of securities traded on GSE are "shares (preference or equities); Debt in the form of corporate bonds (and notes), municipal bonds (and notes), government bonds (and notes); and Close-end unit trusts and mutual funds" (GSE, 2016). GSE has also established Ghana Alternative Market with the objective of assisting SMEs to gain access to the capital market which had four listed SMEs as at December 2015. Moreover, the exchange has also established Ghana Fixed Income Market with the primary aim of providing dedicated market for fixed income securities.

At the end of 2015, fifteen (15) corporate bonds and ninety-seven (79) Government bonds were traded on the Exchange (GSE, 2016). According to the Ghana Stock Exchange 25th

Anniversary Public Lecture held on 11th January 2016, a total amount of GH¢ 2.1 billion has been realised as an equity finance through the GSE. Prior to 2011, the GSE All-share index was the main stock index of GSE with base index value of 10,000. In January 2011, GSE replaced GSE-ASI by Ghana Stock Exchange Composite Index (GSE-CI) with base index value of 1,000. However, some brokers have established their own index, for instance Databank Stock Index (DSI) and CAL Brokers Limited (CBL) All-Share Index.

The equities market capitalisation of the GSE since 2000, has increased tremendously from GH¢365.5 million in 2000 to a value of GH¢57,116.87 million as at December 2015. However, total market capitalization went down by 11.24% from December 2014 value of GH¢64,352.42 million to December, 2015 value of GH¢ 57,116.87 million. A summary report on the yearly market capitalization from 2000 to 2015 is depicted in Figure 3.3.

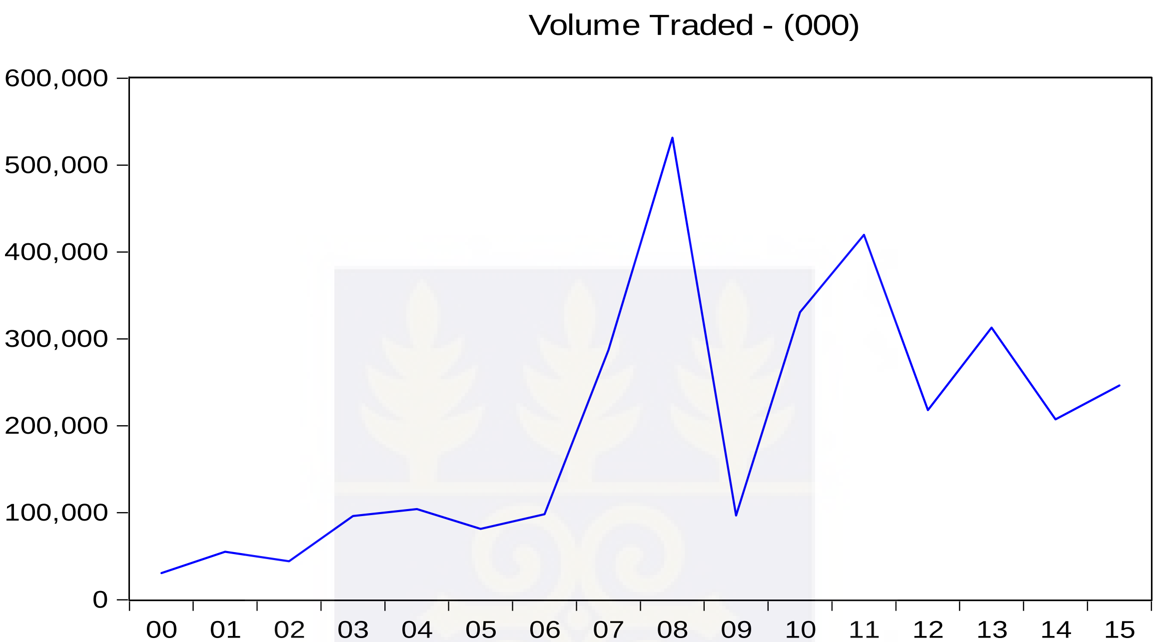
Figure 3.3: A Graph of Yearly Market Capitalization of GSE from 2000 – 2015



Source: GSE Annual report, 2016

Yearly volumes traded have not been encouraging even though volumes traded have increased significantly from 222,000 to 2,464,283,600 as at December 2015. Summary reports on volume traded since the year 2000 is depicted in Figure 3.4.

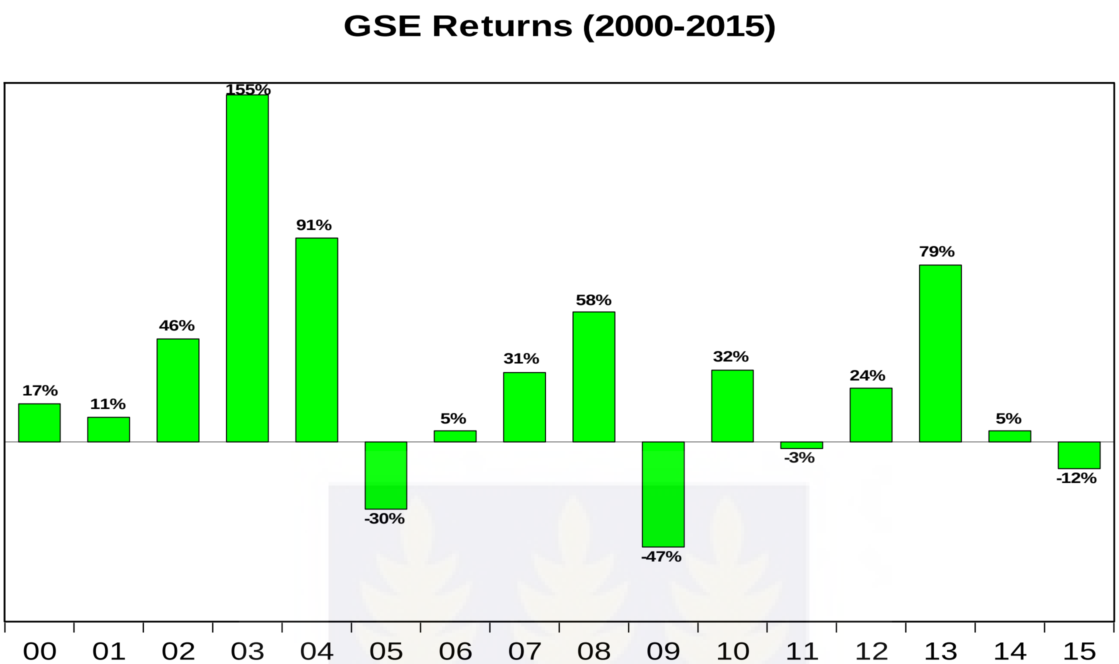
Figure 3.4: A Graph of Yearly Market Trading Volumes of GSE from 2000 – 2015



Source: GSE Annual report, 2016

The Exchange has extremely performed well in terms of capital gains. For instance, the Exchange recorded annual returns of 155%, 91% and 79% in 2003, 2004 and 2013 respectively. However, since 2000, the index has documented four negative annual returns (Specifically in 2005, 2009, 2011 and 2015). It can be observed that the market's worst performance since 2000 was recorded in the year 2009 (−47%) which can be attributed to the 2008 financial crises. The GSE – index annual returns since 2000 are depicted in Figure 3.5.

Figure 3.5: A Graph of GSE – Index Annual Returns from 2000 – 2015



Source: GSE Annual report, 2016

3.5 Variables

The primary objective of this study is to test the rationality of market participants on GSE by investigating for an evidence of overconfidence behavioural bias on GSE. The selection of the variables is influenced by previous studies on overconfidence bias, stock returns, trading volumes, returns volatility and macroeconomic variables relationships. The variables used to investigate the overconfidence bias include endogenous variables and exogenous variables (control variables). Moreover, all the variables used in this study are converted into their natural logarithm form for the analysis and this is adopted because the operation of taking a log constitutes a non-linear transformation (Brooks, 2008).

According to Brooks (2008), the employment of non-stationary data can lead to unreliable estimation and spurious correlation and regression. In order to check for the stationarity of the endogenous and control variables, Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test and Kwiatkowski, Phillips, Schmidt, & Shin (KPSS) test are employed. All variables is tested for stationarity at level and if not stationary then the first difference is considered under assumption of intercept and trend, without trend but intercept and with neither intercept nor trend.

3.5.1 Endogenous Variables

In this study, monthly market-wide detrended logged trading volume (proxy for trading activities) and monthly GSE – index returns (proxy for market returns) are the endogenous variable for the analysis. These variables are used due to Gervais & Odean (2001), Statman et al. (2006) and Chuang & Lee (2006) empirical arguments that overconfidence bias arises from previous markets returns and leads to market participants trading more or less in successive periods.

3.5.1.1 Monthly Detrended Logged Trading Volume (*MDLTVOL*)

In the literature, several researchers have used different indicators in shares, value and turnover ratios as proxy for trading volume. Among these are: Aggregate Share Volume (Hiemstra & Jones, 1994); Individual Share Volume (Epps & Epps, 1976); Individual Dollar Volume (Lakonishok & Vermaelen, 1986); Relative Individual Dollar Volume (Tkac, 1996), Individual Turnover (Stickel & Verrecchia, 1994); Aggregate Turnover (Statman et al., 2006); and Total Number of Trades (Conrad, Hameed & Niden, 1994).

In this study, logged aggregate share trading volume is used as an indicator for trading activities since it is documented in the literature that logged trading volume removes the influence of growth (Statman et al., 2006). The availability of only monthly data of trading volume in shares to the researcher also necessitate the use of trading volume in shares as proxy for trading activities on Ghana stock market. The monthly log trading volume ($MLTVOL$) is non-stationary at level (see Appendix A) and so following Statman et al. (2006) and Zaiane & Abaoub (2009), the log trading volume is detrened.

In addition to non-stationary of the log trading volume, several studies have provided empirical evidence of strong linear and non-linear time trend in times series of trading volume (Gallent, Rossi & Tauchen, 1992; Chen et al., 2001). According to Statman et al. (2006), the linear time trend detrending methodologies seems not flexible enough for trading volume time series so following Statman et al. (2006) and Zaiane & Abaoub (2009), Hodrick-Prescott (1997) algorithm (HP) is employed to detrend the log trading volume. Statman et al. (2006) explains that the HP detrending of log trading volume helps to eliminate the correlation between the level of the trend and volatility around the trend.

The HP filter is a smoothing method that is widely employed by macroeconomists to obtain a smooth estimate of the long-term component of a series. The HP filter was firstly introduced by Hodrick and Prescott in their working paper on the post-war U.S business cycles in the early 1980's which was later published in 1997. The HP filter methodology of detrending series is two-sided linear filter that smooth a series by minimizing the variance of the series. For instance, the HP computes the smooth series monthly detrended logged trading volume ($MDLTVOL_t$) of the monthly logged trading volume ($MLTVOL_t$) series by minimizing the variance of $MLTVOL_t$ around $MDLTVOL_t$ subject to a penalty that constrains the second difference of $MDLTVOL_t$. Thus, the HP filter chooses $MDLTVOL_t$ to minimize:

$$\sum_{t=1}^{T}(MLTVOl_{t} - MDLTVO_{t})^2$$

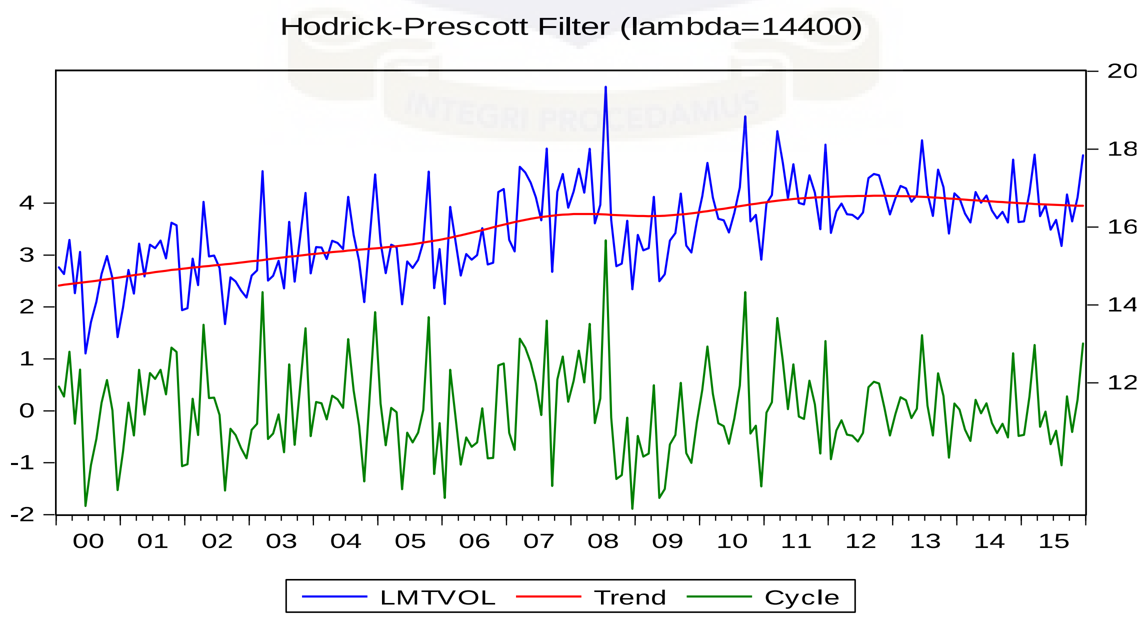
$$+\lambda\sum_{t=2}^{T-1}\left((MDLTVO_{t+1} - MDLTVO_{t}) - (MDLTVO_{t} - MDLTVO_{t-1})\right)^2 \qquad (3.1)$$

Note: MDLTVOL = monthly detrended logged trading volume; MLTVOL = monthly logged trading volume

The penalty parameter λ controls the smoothness level of the series $MDLTVOL_t$. Following Hodrick & Prescott (1997) and Zaiane & Abaoub (2009), the λ is set to be equal to 14,400. It worth noting that the larger λ, the smoother the series $MDLTVOL_t$. Thus, the detrending of the trading volume is performed to obtain a stationary series (see Appendix A) and so therefore the detrended logged trading volume is used for the analysis.

Figure 3.6 shows the original log trading volume series (blue line), the smooth trend (red line) and the stationary series (green line). The stationary series referred as cyclical in the figure is what is employed in the VAR model.

Figure 3.6: A Graph showing the Detrending of Logged Market Trading Volume



Note: LMTVOL = Logged Market Trading Volume

3.5.1.2 Thin trading and Monthly Market Return (*MRET*)

It is reported by several studies (such as Lo & MacKinlay, 1990; Stoll & Whaley, 1990; Miller et al., 1994) in the literature that thin (infrequent) trading may cause autocorrelation in the return series. Thin trading is also indicated in the literature to be a common characteristic of most emerging markets and GSE is no exception. The issue is that the absence of a price change between any two moments may be explained as being caused by the absence of a price reaction to new information rather than being due to infrequent trading. It is worth stating that it is explained in the literature that thin trading is very evidence in high frequency data such as hourly, daily and weekly.

However, some studies such as Darwish (2012) have indicated that low frequency financial data such as monthly observation may overcome thin trading since low frequency data have enough time frame for price change to be observed. As a result, the thin trading correction as proposed by some researchers is not effected for this study due to the use of monthly data.

The monthly GSE – index return is obtained from the monthly closing value of GSE – index. The study employs the Ghana Stock Exchange All-Share Index (GSE – ASI) monthly closing values from January 2000 to December, 2010. However, after January 4, 2011, the GSE – ASI is replaced with the Ghana Stock Exchange Composite Index (GSE – CI). These indexes reflect the average price movements in all the equities listed on the stock market. The employment of the index data presents the inborn advantage that the observations used are not biased by any peculiar effects taking place within individual stocks (Mensah et al., 2016). The monthly return is obtained by employing returns continuously compounded formulae:

$$MRET_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (3.2)$$

Note: $\mathrm{MRET_t}$ = monthly GSE – index returns at time t; $\mathrm{P_t}$ = monthly GSE – index value at time t.

From equation 3.2, P_t is the closing GSE – index value at month t, P_{t-1} is the closing GSE – index at lag one and ln denotes the natural logarithm. The continuously compounded return is adopted because of time addictive and irrelevant of the frequency of compounding (Brooks, 2008). Also, the monthly returns ($MRET$) was found to be stationary (see Appendix A).

3.5.2 Control (Exogenous) Variables

Three main control variables are used in this study, namely, monthly market volatility, inflation and interest rate. The theoretical explanations and the methodology used to measure these variables are explained below. However, it is worth pointing out that monthly market volatility was found to be stationary at level (see Appendix A) whiles inflation and interest rate were not stationary at level but become stationary at first difference (see Appendix A).

3.5.2.1 Market Return Volatility (MSIG)

Return volatility is introduced into the VAR model as a control variable based on Karpoff's (1987) survey of studies on the contemporaneous nexus between trading volume and returns volatility. Karpoff (1987) argued that market participants employ trading volume to forecast future price movement of securities and as a result, a relationship between volume and price movements offers "an insight into structure of financial markets" (Karpoff, 1987, p. 109).

Moreover, the Mixture of Distribution Hypothesis postulates that there exists positive nexus between stock returns and volume since both jointly depend on the volume which reveals the market level of information flow. Therefore, security prices variation can be explained by the flow of information to the market which implies that a positive contemporaneous nexus exist between volumes and return volatility. Poon & Granger (2003) argues that understanding the nexus between trading volume and returns volatility helps in modelling returns distributions appropriately. Many empirical evidences have reported a relationship between trading volume and returns volatility. For instance, Chen et al. (2001) indicated that trading volume acts as a catalyst in reducing stock returns volatility on Chinese Stock Market.

The volatility measure employed in this study follows Statman et al. (2006) and Zaiane & Abaoub (2009) computation of volatility which is based on French, Schwarz & Stambaugh (1987). French, Schwarz & Stambaugh (1987) explains that, assuming "N" days for the month, month t's volatility with r_i representing the ith trading day returns in the month is given by:

$$MSIG_t{}^2 = \sum_{i=1}^{N} r_i{}^2 + 2\sum_{i=1}^{N-1} r_i r_{i+1} \qquad (3.3)$$

3.5.2.2 Inflation and Interest Rate (Macroeconomic Variables)

A vast number of empirical studies in literature have documented a significant nexus existing between returns and macroeconomic variables in both advanced countries and emerging countries. Specifically, quite a number of empirical studies have found a significant nexus between stock performance and macroeconomic on Ghana stock market (such as Kumornu & Owusu-Nantwi, 2011; and Issahaku et al., 2013).

Based on these empirical evidence, inflation and interest rate variable is introduced into the VAR model. Following Issahaku et al. (2013), the log of monthly consumer price index ($LCPI$) is used as proxy for inflation and the log of 91-day Treasury bill rate ($LTBR$) as proxy for interest rate. However, $LCPI$ (proxy for inflation) and $LTBR$ (proxy for interest rate) were found not to be stationary hence the first differences ($\Delta LCPI$ and $\Delta LTBR$) of these variables which were found to be stationary were used for the analysis (see Appendix A).

3.6 Empirical Methodology

In this study, overconfidence bias is tested by employing the Vector Autoregression (VAR) model and its associated impulse response function. This model is adopted from Statman et al. (2006) empirical model they used to investigate overconfidence bias.

3.6.1 The General Vector Autoregressive Model (VAR)

The VAR model used in this study was adopted from Statman et al. (2006) paper which studied overconfidence bias in the US. Thus, Statman et al. (2006) constructed a VAR model to investigate the lead-lag relationship between market return and market trading volume. The general form of VAR model employed by Statman et al. (2006) is given by:

$$\boldsymbol{Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=o}^{L} B_l X_{t-l} + e_t} \qquad (3.4)$$

where Y_t is a $n \times 1$ vector of period t endogenous observations, for instance, they used turnover and return. X_t is a vector of control variables observations (they used volatility and portfolio rebalancing) at time t and e_t is $n \times 1$ residual vector. The regression coefficients, A_k estimate the time series nexus between endogenous variables and its lags, B_l estimate the nexus between endogenous variables and the control variables, where k is the number of lagged endogenous observations and l is the number of lagged exogenous observations. K is the last or the nth lag observation of the endogenous variables considered and L is the last lag or nth lag observation of the exogenous variables considered.

3.6.2 Theoretical framework for the model

According to Statman et al. (2006), the VAR model was employed based on Odean (1998) and Gervais & Odean's (2001) paper. Odean (1998) predicts that high total market returns make some investors overconfident about the precision of their information and investment strategies. Gervais & Odean (2001) develop a multi-period market model to assess how market participants learn about their abilities. They also tested how self-attribution bias leads to overconfidence bias. They indicated that overconfidence level of investor's changes and can be attributed to previous market gains and losses. For instance, in a bull market, market participants easily make gains and as a result traders become more overconfident. They associate the success to their own expertise ignoring the fact that the gains they are enjoying are total market phenomena at that point in time. Thus, aggregate market returns have influence on the overconfidence level of market participants.

Also, Gervais & Odean (2001) indicated that overconfidence bias of market participants leads them to trade more. They explained that although market returns is market wide, market participants mistakenly ascribe gains to their own skills to select portfolios and stocks. Based on this empirical evidence, Statman et al. (2006) postulated that if the lag terms of market return are significant in explaining current market trading volume then that is evidence of overconfidence bias. Therefore, Statman et al. (2006) constructed a VAR model to investigate the lead-lag relationship between market returns and market trading volumes.

The VAR model used by Statman et al. (2006) to measure overconfidence is valid since it rests on two major implications of overconfidence documented on financial markets by several researchers. Thus, the VAR model used employs one of the variables reported to be a source of overconfidence (market returns) and also one variable reported to be the predominant effect of overconfidence of investors on financial markets (excessive trading). Also, the VAR model is suitable for this analysis since it does not put any restrictions on any of the two main variables of interest (trading volume and returns) as to which of the variables are exogenous or endogenous but rather all variables are considered endogenous. The VAR model also permits for a covariance structure to exist in the residual vector that captures the contemporaneous correlation between control variables which helps to have a better result than other structural models when control variables are introduced into the model.

3.6.3 VAR Model specification for the study

It is worth pointing out that the adopted VAR model and its associate impulse response function is employed to address the research objective one, which is investigating an evidence of overconfidence bias on GSE. As indicated above, the VAR model employed for this study is adopted from Statman et al. (2006) and modified with the introduction of macroeconomic variables. Vector Autoregressive model (VAR) is a system regression model constructed to investigate the lead-lag relationships among variables and Sims (1980) popularised this model in the econometrics literature as the univariate autoregressive model generalisation (Brooks, 2008). Typically, a VAR is used to estimate several equations simultaneously without indicating which of these variables are endogenous and exogenous.

Based on the general VAR model (equation 3.4), a market version of the general model in Equation (3.5) which contains two endogenous variables, market monthly detrended trading volume and market return, and three control variables, market volatility, inflation and interest rate is constructed as:

$$\begin{bmatrix} MDLTVOL_t \\ MRET_t \end{bmatrix} = \begin{bmatrix} \alpha_{MDLTVOL} \\ \alpha_{MRET} \end{bmatrix} + \sum_{k=1}^{K} A_k \begin{bmatrix} MDLTVOL_{t-k} \\ MRET_{t-k} \end{bmatrix}$$

$$+ \sum_{l=0}^{L} B_l \begin{bmatrix} MSIG_{t-l} \\ \Delta LCPI_{t-l} \\ \Delta LTBR_{t-l} \end{bmatrix} + \gamma dum08 + \begin{bmatrix} e_{MDLTVOL,t} \\ e_{MRET,t} \end{bmatrix} \qquad (3.5)$$

where $MDLTVOL_t$ is the monthly detrended logged trading volume at month t; $MRET_t$ is the monthly GSE – index return at month t; $MSIG_t$ is the market returns volatility at month t; $\Delta LCPI_t$ is the proxy for inflation at month t, $\Delta LTBR_t$ is the proxy for interest rate at month t and $dum08$ is the 2008 financial crisis dummy variable. The $dum08$ is considered due to volatility clusters (See Figure 3.1 and Figure 3.2) that manifest in monthly GSE – index returns ($MRET$) and monthly trading volume ($MVOL$) which may be a result of the 2008 global financial crises. Thus, in order to remove the possible impacts of the 2008 global financial crises from the model, a dummy variable, $dum08$ that takes 1 for January, 2008 to December, 2010 (otherwise, 0) is introduced.

3.6.3.1 Impulse Response Functions (IRF)

The VAR model indicates which of the variables used in the model have statistically significant impacts on each of the variables future values in the system. However, the overall impact of the endogenous and the control variables lags are not fully captured by the VAR model. Therefore, several researchers employ the impulse response function which uses all the coefficient estimates of VAR to trace the complete impact of a residual shock (one sample standard deviation) on the endogenous variables is performed to ascertain the full impacts of all the variables used in the VAR.

Impulse response function traces the impacts of one standard deviation shock to the residual of the endogenous variables on the endogenous variables' current and future values through the dynamic structure of the VAR model (Statman et al., 2006). For instance, Equation (3.5) have: two endogenous variables, namely, market trading volume and market index returns; and also three control variables, namely, market returns volatility, inflation and interest rate. For instance, a shock of one standard deviation to any of the endogenous variable residual, say $e_{MDLTVOL,t}$would instantaneously vary the trading volume current value ($MDLTVOL_t$) and consequently affect the future values of $MDLTVOL_t$. Moreover, this shock would also influence the market returns ($MRET_t$) through the A_k coefficient due to the fact that the $MDLTVOL_t$ lagged values are in both equations.

The primary purpose of this study is to investigate market evidence of overconfidence bias hypothesis on GSE employing lead-lag relationship between market returns and trading volume and as a result a one-standard deviation shock is applied to the endogenous variables residual to ascertain the full impact of the variables in the VAR model. Thus, employing all the VAR estimates and its dynamic structure, the responds of market detrended logged trading volume and market returns to the endogenous variables residual shock is graphed. Therefore, the impulse response function gives a simple picture as to how endogenous variables respond to these residual shocks over time.

3.6.3.2 Optimal Lag Selection

Deciding on the appropriate lag order for autocorrelation functions is one of the crucial decisions to make to ensure a valid estimation results. However, financial theory and for that matter overconfidence bias theories do not specify the suitable lag length that a researcher should adopt for a VAR model and its associated dynamic analysis. The model used in this study is a VAR system and as a result an optimal lag is necessary for valid estimation results. Therefore, two main approaches are employed to obtain the optimal lag for the VAR model. Thus, the cross-equation restrictions (Likelihood Ratio (LR) test) and information criteria approach.

3.6.3.2.1 Cross-equation Restrictions (Likelihood Ratio (LR) Test)

In order to employ the LR test to determine the optimal lag structure, a sequential modification is performed on the LR. Beginning from the possible highest lag, a jointly zero hypothesis on the estimated coefficients of equation (3.6) is conducted:

$$\boldsymbol{LR} = (\boldsymbol{T} - \boldsymbol{n}\ )\left[\boldsymbol{Log}\left|\widehat{\textstyle\sum_r}\right| - \boldsymbol{log}\left|\widehat{\textstyle\sum_u}\right|\right] \qquad (3.6)$$

Where $\left|\widehat{\sum_r}\right|$ refers to the determinant of the variance-covariance matrix resulting from the residuals of the restricted VAR model (say lag 4) estimation. Also, $\left|\widehat{\sum_u}\right|$ refers to the variance-covariance matrix determinant resulting from the unrestricted VAR model (say lag 12) estimation. The T refers to the sample size whiles the m refers to the number of parameters per equation. $(T - m)$ in Equation (3.6) is Sims (1980) modification for small sample size. The test statistics has χ^2 distribution with the number of restrictions as the degrees of freedom. To achieve the optimal lag, this test "compare the modified LR statistics to the 5% critical values starting from the maximum lag, and decreasing the lag one at time until the first rejection is obtained. The alternative lag order from the first rejected test is selected as optimal lag" (Eviews 9, User's Guide).

3.6.3.2.2 Information Criterion

Another way to choose the optimal lag is to select the model order that minimizes information criterion value. The information criterion is performed by fitting VAR (p) models with different lag length on the data and the lag length (p) that provides the minimum value of the information criterion is selected. The models used for the information criterion selection of optimal lags include Akaike Information Criterion (AIC), Schwarz-Bayesian (SC) and Hannan-Quinn Criterion (HQ).

$$
\begin{aligned}
AIC &= -\frac{2\ell}{T} + \frac{2k}{T} \\
SC &= -\frac{2\ell}{T} + \frac{k}{T}(\ln T) \qquad (3.7) \\
HQ &= -\frac{2\ell}{T} + \frac{2k}{T}\ln(\ln T)
\end{aligned}
$$

where $\ell = -\frac{T}{2}(1 + \ln(2\pi) + \ln(\hat{u}'\hat{u}/T))$, k refers to the number of estimated parameters, T is the sample size. According to Brooks (2008), SC embodies much stiffer penalty term than AC while HC is somewhere in between.

3.6.4 Granger Causality Test

The granger causality model is used to address the research objective two of examining whether trading volume has impact on stock returns or stock returns have impact on trading volume or both exist on GSE. In this study, a granger causality test is conducted alongside the VAR model estimation to detect the causality between returns and trading volume on GSE as well as to validate the results of VAR model. The adoption of the granger causality is partly motivated by Hiemstra & Jones (1994) argument that the trading volume and returns causal nexus can help to explain stock price movement and changes in trading volume. It partly also rests on Chuang & Lee (2006) argument that overconfidence causes a positive causal relation between stock returns and trading volume.

Granger (1969) proposes an approach to answer the question whether a series say x_t causes another series say y_t or whether y_t causes x_t. Thus Granger (1969) approach basically seek to know whether the current values of y_t is explained by past values of x_t. Therefore, x_t is claim to Granger-cause y_t if lagged $x's$ explain current $y's$ and as a result x_t helps in the prediction of y_t. Specifically, a bivariate Granger causality test of the form equation (3.8) and (3.9) is adopted to empirically test the causal relation between trading volume and returns on GSE.

$$\boldsymbol{MDLTVOL_t = \alpha_{11} + \sum_{j=1}^{p} \beta_{11j} MDLTVOL_{t-j} + \sum_{j=1}^{p} \beta_{12j} MRET_{t-j} + \varepsilon_{1t}} \qquad (3.8)$$

$$\boldsymbol{MRET_t = \alpha_{21} + \sum_{j=1}^{p} \beta_{21j} MDLTVOL_{t-j} + \sum_{j=1}^{p} \beta_{22j} MRET_{t-j} + \varepsilon_{2t}} \qquad (3.9)$$

Where $MDTVOL_t$ is the market trading volume at month t, $MRET_t$ is the market-wide return at month t, The coefficients, β_{12j} and β_{21j} estimate the time series impacts between returns and trading volume. j is the number of lagged observations and p is the last or the nth lag observation considered. α_{11} and α_{21} are constant whiles ε_{1t} and ε_{2t} are the error terms. Based on the model above, a joint hypothesis of the form (3.10) is tested and the F-statistics (Wald Statistics) is reported:

$$\boldsymbol{\beta_{12j} = \beta_{21j} = 0} \qquad (3.10)$$

The null hypothesis for this test is that $MRET_t$ does not granger-cause $MDLTVOL_t$ with regard to equation (3.8) and also $MDLTVOL_t$ does not granger-cause $MRET_t$ with respect to equation (3.9). The decision criterion in this test is that, if the corresponding p-value of the F-statistics test is less than 1% or 5% or 10% significance level, the null is rejected.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

The aim of this chapter is to present and discuss results obtained using the data and methodologies explained in the previous chapter. In this chapter, descriptive statistics, the market VAR estimation and results and the Granger Causality results are presented and discussed.

4.2 Descriptive Statistics

The summary statistics on monthly market-wide variables used for this study is presented in Table 4.1. Thus, the descriptive statistics on monthly trading volume ($MDLTVOL$), monthly GSE – index return ($MRET$), market volatility ($MSIG$), inflation ($\Delta LCPI$) and interest rate ($\Delta LTBR$) are presented in Table 4.1. The Table 4.1 shows the descriptive statistics on the above variables for the full sample period (January, 2000 – December, 2015) and the financial crisis sub-sample period (January, 2008 – December, 2010).

The $MDLTVOL$ (and monthly raw trading volume (unreported)) for the full sample period indicated positive skewness. This suggests that the distribution of the trading volume variable is skewed to right and leptokurtic. The mean market–wide monthly raw trading volume in shares for the full sample period is 16,464,250 (unreported). The descriptive on $MDLTVOL$ indicates kurtosis greater than three for the full sample. The normality hypothesis is rejected by the Jarque-Bera statistics for trading volume over the full sample period at 5% significance level. This empirical evidence of non-normality of trading volume is consistent with Jlassia, Naouib & Mansourc (2013) descriptive results of 27 economies (11 advanced markets, 4 Latin Amercian markets, 7 Asian markets and 5 emerging markets) using data from 2000 to 2012.

Table 4.1: Descriptive Statistics Results

	MDLTVOL	*MRET*	*MSIG*	*ΔLCPI*	*ΔLTBR*
Full sample period (2000 to 2015) – 192 Obs					
Mean	-0.012952	0.015577	0.001309	0.005782	-0.002036
Median	-0.074492	0.009617	0.000309	0.012744	0.000000
Maximum	3.283529	0.201080	0.020403	1.256102	0.282349
Minimum	-2.041713	-0.323124	-3.63E-05	-1.388581	-0.303929
Std. Dev.	0.852264	0.058172	0.002593	0.163684	0.068536
Skewness	0.533777	-0.711575	3.846768	-3.237700	0.215836
Kurtosis	3.869594	9.926166	21.93949	63.49877	7.392924
Jarque-Bera	15.16690	399.9770	3343.158	29616.26	155.8730
Probability	0.000509	0.000000	0.000000	0.000000	0.000000
Financial crisis sub-sample period – dum08 (2008 to 2010) – 36 Obs					
Mean	-0.103118	0.003081	0.002552	0.011031	0.004019
Median	-0.238697	0.010954	0.001294	0.014511	0.000000
Maximum	3.283529	0.174099	0.020403	0.031433	0.217065
Minimum	-1.886298	-0.323124	1.46E-08	-0.015222	-0.174353
Std. Dev.	1.095621	0.088496	0.003996	0.013065	0.084805
Skewness	0.959709	-1.425715	2.903729	-0.503142	0.575067
Kurtosis	4.278534	6.810323	12.48229	2.257077	3.956476
Jarque-Bera	7.978226	33.97382	185.4607	2.346812	3.356487
Probability	0.018516	0.000000	0.000000	0.309312	0.186702

Note: Obs = Observations; MDLTVOL= monthly detrended log trading volume; MRET= monthly GSE-index returns; MSIG= market volatility; ΔLCPI = inflation (first difference of log CPI), and ΔLTBR = interest rate (first difference of log 91-day T.Bill rate)

The full sample mean for the monthly GSE – index returns ($MRET$) is 1.6%; and a simple annualised average return is $12 \times 1.6 = 19.2\%$. The kurtosis value of 9.926166 for the full sample period is greater than three which indicates that GSE – index returns have significant leptokurtosis. The market returns are negatively skewed indicating that the distribution has a long left tail. Moreover, the standard deviation that measures the GSE stock index's return volatility is high compared to mean return. Likewise, the Jarque-Bera test result rejects the normality hypothesis of monthly returns at 1% significant level. The high kurtosis value observed follows the descriptive summary findings on emerging economics of Jlassia et al. (2013). This empirical finding of non-normality of GSE – index monthly returns is consistent with Jlassia et al. (2013), the conventional theory (Fama, 1965, 1970) and it is also consistent with descriptive empirical evidence of Appiah-Kusi & Menyah (2003) when they tested the weak-form market efficiency of eleven African stock markets including Ghana.

Additionally, Table 4.1 shows the summary statistics on the control variables, namely; volatility ($MSIG$), inflation ($\Delta LCPI$), and interest rate ($\Delta LTBR$). The results of the control variables over the full sample period show a positive mean return with the exception of interest rate. In terms of skewness, $MSIG$ and $\Delta LTBR$ both exhibit return distributions which are positively skewed over the full sample period. $\Delta LCPI$ on the other hand exhibits a negative skewness over the full sample which means that it has a long left tail. The null hypothesis of normality is rejected for these variables over the full sample period at 5% level using the Jarque-Bera statistics. The negative skewness of inflation and non-normality of the macroeconomic variables follows the descriptive statistics of Kuwornu & Owusu-Nantwi (2011) when they study the relationship between macroeconomic variables (using consumer price index (proxy for inflation), crude oil price, exchange rate and 91-day Treasury bill rate (as a proxy for interest rate)) and market returns on the GSE.

The mean raw trading volume (unreported) for the financial crisis sub-sample period is 26,625,916. The kurtosis value for the $MDLTVOL$ is greater than three and thus, the trading activity variables have significant leptokurtosis. The maximum trading volume over the full sample period is observed in the sub-financial crisis period. The normality hypothesis of $MDLTVOL$ is rejected by the Jarque-Bera statistics at 5% significant level over the financial crisis sub-sample period.

The mean return of the financial crisis period is approximately 0.3% and a simple annualized return is 3.6%. Over the financial crisis sub-sample period, the market returns is also negatively-skewed and the kurtosis values are greater than three and thus, the index has higher peaks or leptokurtic relative to the normal distribution. The minimum return (-0.323124) for the full sample period is observed in the sub-financial crisis period. Financial crisis sub-sample period returns volatility is higher as compared to the standard deviation for the whole sample period. This implies that volatility on GSE is high during financial crisis periods. Moreover, the normality hypothesis for the market-wide monthly returns in the sub-sample period is rejected at 1% significant level which means the return distribution does not follow normal distribution. These empirical evidences of minimum return and maximum trading volume being observed in this financial crisis sub-sample also motivated the dummy variable introduction. The summary statistics on the control variables over the financial crisis sub-sample period are also reported in Table 4.1.

4.3 VAR Estimation and Test Results

4.3.1 Optimal Lag Selection

The determination of optimal lag length is important for a valid VAR model results. The overconfidence bias theories do not specify the optimal lag to use for the VAR model.

Therefore the optimal lag order for the VAR analysis for this study is obtained following the LR and information criteria test. Eviews computation of the likelihood ratio and different version of information criteria until the 12th lags is depicted in Table 4.2. Table 4.2 indicates that both Likelihood Ratio (LR) and Akaike Information Criterion (AIC) reveals that the third lag is the optimal lag for the endogenous variables. Using the three endogenous variables, the model is developed by adding the lags of the control variables and then compares the information criteria of these models. However, it turns out that the optimal lag length for the model with both the endogenous and control variables is also three lags.

Table 4.2: VAR Lag Order Selection Criteria Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	51.03493	NA	0.002644	-0.260282	0.242160	-0.056511
1	83.27303	58.64784	0.001923	-0.579356	-0.005137*	-0.346475*
2	84.74756	2.649166	0.001979	-0.550820	0.095177	-0.288829
3	91.65690	12.25725*	0.001916*	-0.583694*	0.134080	-0.292593
4	95.44041	6.626481	0.001922	-0.581248	0.208304	-0.261036
5	97.20003	3.042060	0.001973	-0.555933	0.305396	-0.206611
6	98.26497	1.817008	0.002041	-0.522768	0.410338	-0.144336
7	99.97767	2.883523	0.002097	-0.496923	0.507961	-0.089381
8	103.6625	6.120599	0.002107	-0.493362	0.583299	-0.056710
9	107.6271	6.495596	0.002111	-0.492961	0.655477	-0.027199
10	108.6046	1.579587	0.002188	-0.458810	0.761406	0.036063
11	110.0248	2.262627	0.002257	-0.429659	0.862334	0.094323
12	111.9633	3.044710	0.002315	-0.406365	0.957405	0.146727

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

4.3.2 Market VAR Estimation Results

The results of market VAR system which is used to address the research objective one estimation is reported in Table 4.3. The market VAR system is made up of two endogenous variables: monthly market-wide trading volume ($MDLTVOL$) and monthly GSE – index return ($MRET$); and three control variables: market volatility ($MSIG$), the first difference of inflation ($\Delta LCPI$) and the first difference of interest rate ($\Delta LTBR$). Table 4.3 is arranged into columns for endogenous variables and rows for the lag terms of both endogenous and control variables. For each of the variables, estimated coefficient, standard error, test statistics and p – value results are reported. In order to verify if the variable estimated coefficient is significantly different from zero, the p-values are employed. Thus, variables with reported p – value less than 10% are considered as significant in this study. Also, variables with reported p – value less than 5% or 1% are also considered as highly significant in this study. It is worth stating that the $dum08$ refers to the 2008 global financial crisis sub-sample period and as indicated in the Table 4.3, has no significant statistical impact on the VAR system.

According to Table 4.3, it is documented that the monthly trading volume is not autocorrelated. Thus, the first, second and third lagged market-wide monthly trading volume estimated coefficients are insignificant even though the first lag is positive. It indicates that the monthly market-wide trading volume is not significantly affected by its own behaviour in past months. Using the monthly raw trading volume as a robust check, the results (unreported) indicated that monthly raw trading volume is not autocorrelated. This implies that market participants cannot use past trading volume to predict future trading volume on GSE. This empirical evidence is consistent with Zaiane & Abaoub (2009) results on Tunisian

Table 4.3: Vector Autoregression (VAR) Estimation Results

	$MDLTVOL_t$				$MRET_t$			
	Coeff	St. error	t-stats	p-value	Coeff	St. error	t-stats	p-value
$MDLTVOL_{t-1}$	0.115592	0.078190	1.478351	0.1403	0.007182	0.004581	1.567780	0.1179
$MDLTVOL_{t-2}$	−0.074258	0.078659	−0.944051	0.3458	−0.002958	0.004608	−0.641903	0.5214
$MDLTVOL_{t-3}$	0.045713	0.077905	0.586777	0.5578	0.003782	0.004564	0.828720	0.4079
$MRET_{t-1}$	3.481225***	1.326264	2.624837	0.0091	0.548769***	0.077700	7.062653	0.0000
$MRET_{t-2}$	−2.090180	1.501038	−1.392490	0.1647	−0.195298**	0.087939	−2.220819	0.0270
$MRET_{t-3}$	1.332521	1.316096	1.012480	0.3120	0.196874**	0.077104	2.553345	0.0111
α	−0.052702	0.084665	−0.622476	0.5341	0.006541	0.004960	1.318773	0.1882
$MSIG_t$	−21.06351	26.59476	−0.792017	0.4289	−1.748235	1.558074	−1.122049	0.2627
$MSIG_{t-1}$	7.283127	28.01752	0.259949	0.7951	−0.122848	1.641427	−0.074842	0.9404
$MSIG_{t-2}$	−32.76589	27.44409	−1.193914	0.2334	2.336669	1.607832	1.453304	0.1471
$MSIG_{t-3}$	56.55985**	26.33562	2.147656	0.0325	1.017799	1.542892	0.659670	0.5099
$\Delta LCPI_t$	−0.014645	0.400201	−0.036594	0.9708	−0.020765	0.023446	−0.885636	0.3765
$\Delta LCPI_{t-1}$	0.180125	0.423454	0.425371	0.6708	−0.003573	0.024808	−0.144026	0.8856
$\Delta LCPI_{t-2}$	−0.316843	0.423732	−0.747744	0.4551	−0.032261	0.024825	−1.299566	0.1947
$\Delta LCPI_{t-3}$	0.042251	0.402121	0.105071	0.9164	−0.002433	0.023559	−0.103292	0.9178
$\Delta LTBR_t$	−1.817571*	1.072189	−1.695195	0.0910	0.012491	0.062815	0.198846	0.8425
$\Delta LTBR_{t-1}$	1.242308	1.168274	1.063371	0.2884	0.040995	0.068444	0.598958	0.5496
$\Delta LTBR_{t-2}$	−1.721496	1.173604	−1.466846	0.1434	−0.071437	0.068756	−1.038983	0.2996
$\Delta LTBR_{t-3}$	0.942202	1.095373	0.860165	0.3903	−0.080293	0.064173	−1.251187	0.2117
$dum08$	−0.068776	0.171285	−0.401528	0.6883	−0.007177	0.010035	−0.715212	0.4750

Note: ***,** and * indicates significant at 1%, 5% and 10% level respectively; Coeff = coefficient; St. error = Standard error; t-stats = test statistics. Where: MDLTVOL= monthly detrended log trading volume; MRET= monthly GSE-index returns; MSIG= market volatility; ΔLCPI = inflation (first difference of log CPI), and ΔLTBR = interest rate (first difference of log 91-day T.Bill rate) stock market when they also used detrended trading volume and returns to examine overconfidence bias in Tunisian market. However, this result contradicts with Statman et al. (2006) findings from advanced market. Statman et al. (2006) used share turnover as proxy for trading volume and they reported that turnover is autocorrelated, with a highly significant first lagged coefficient of 0.284.

More importantly, the first lag of market returns is found to have highly significant positive impacts on market trading volume. The significant impact of the market return on the market trading volume only exists in the first lag whiles the second and third lag of market return are not statistical significant. The highly significant positive first lagged market return (3.481225) impact on the market-wide trading volume at 1% confidence level demonstrates the overconfidence hypothesis that high market returns triggers overconfidence of investors which makes them trade more in subsequent periods. The empirical evidence of positive highly significant nexus between current market trading volume and first lag market returns is the major findings of this study. This empirical finding indicates that GSE – index past market returns triggers overconfidence of market participants on GSE which makes them trade more in subsequent periods. This empirical result is consistent and also confirms the overconfidence hypothesis results of empirical studies reported in the finance literature by scholars such as Statman et al. (2006), Chuang & Lee (2006), Zaiane & Abaoub (2009) and Metwally & Darwish (2015). Statman et al. (2006) for instance employed monthly shares turnover, returns, market volatility and dispersion reported highly significant first lag coefficient (0.819) and second lag coefficient (0.433). Statman et al. (2006) explained this finding as an evidence of overconfidence on US stock markets. Also, Zaiane & Abaoub (2009) following Statman et al. (2006) examined overconfidence bias on Tunisian stock market reported only one significant coefficient (the fifth lag) of monthly returns impacts on trading volume. They interpreted this result as evidence of overconfidence but indicated it is remarkably weak.

According to Table 4.3, the $MRET$ exhibits autocorrelation which implies that market return prediction anomaly exists on GSE. Thus, estimated coefficients for first, second and third lags of $MRET$ are highly significant. This means that past monthly market returns influence the behaviour of current period's market returns. Specifically, market returns are significantly positively influenced by its first lag. This finding is also consistent with Mensah et al. (2016) evidence of the GSE – index returns exhibiting a significant autocorrelation. The influence of past market returns on the current market returns imply that the investors on GSE can use past market returns to predict future returns. This result is inconsistent with the most result from advanced markets. For instance, Statman et al. (2006) found no autocorrelation on monthly market returns in US.

Considering the contemporaneous nexus between monthly return volatility and monthly trading volume, results in Table 4.3 indicate that volatility has no significant influence on trading volume at contemporaneous level. This finding implies that the GSE market has liquidity challenges since return volatility has no contemporaneous effect on trading volume. This empirical result is inconsistent with the findings of Karpoff (1987), Statman et al. (2006) and Zaiane & Abaoub (2009) on the same subject matter. However, return volatility has positive highly significant impact on trading volume at lag three.

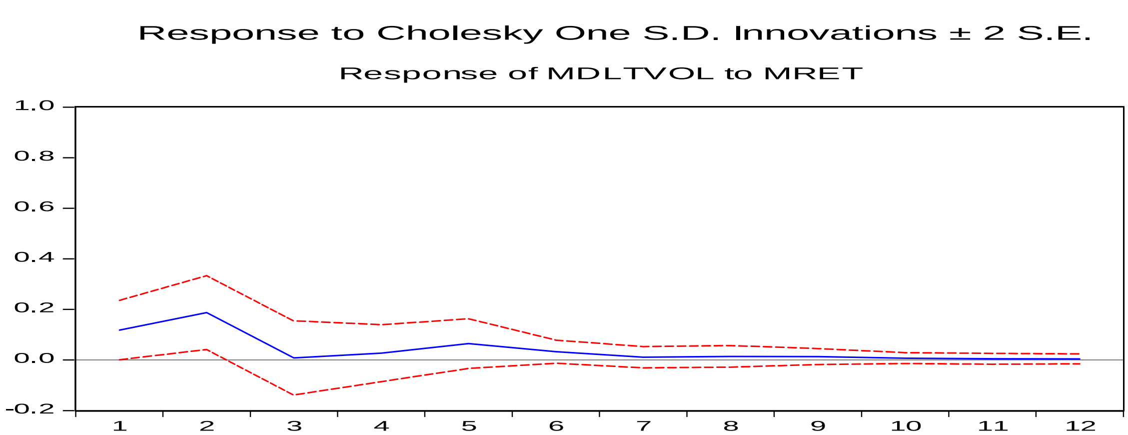
With respect to the relationship between macroeconomic variables and trading volume, interest rate has negative significant impacts on the trading volume at contemporaneous level. According to Adjasi et al. (2008), the negative statistical significant inflation estimates implies that under a good-looking Treasury bill rates, stock analyst forecast investors being rational may shift much of the funds at their disposal from stocks to treasury bills and as a result affect stock market trading activities.

Moreover, in order to ensure the coefficients reported above are significant, a VAR Residual Portmanteau Tests for Autocorrelations is performed and the null of no residual autocorrelations up to lag 30 cannot be rejected (see Appendix B).

4.3.3 Impulse Response Functions (IRF)

Impulse Response Function which uses all the coefficient estimates of the VAR to trace the complete impact of a residual shock (one sample standard deviation) on the endogenous variables is performed. Figure 4.1 consist of IRF graph employing all the VAR estimates depicted in Table 4.3. The vertical axis measures the percentage increase in endogenous variable with respect to a shock. The blue line in the graph outlines the response of the endogenous variable to a shock whilst the red line is the two standard error band. The impulse function becomes zero in the long term since the monthly market-wide trading volume is detrended (Statman et al., 2006).

Figure 4.1: Impulse Response Function (IRF) Graph of the Market-wide VAR model



Note: MDTVOL = monthly market-wide trading volume; MRET = monthly GSE-index returns

Figure 4.1 depicts the response of monthly trading volume to a residual shock of monthly market returns. The Figure 4.1 shows that the response by market trading volume to a residual shock of returns exists until the seventh period. Precisely, in lag one and two, the response is evidently large and positive. The shock of market return residual brings 0.12% increase in market trading volume at first lag and 0.19% increase at second lag. Statman et al. (2006) interpret this evidence as market returns influence on overconfidence level of investors which trigger changes in their subsequent trading activities. This confirms the key finding of this study established in the VAR model results. However, there are few behavioural or rational expectations models that are consistent with the positive lead – lag relationship between returns and volume such as portfolio rebalancing and heterogeneous interpretation of informational (Sequential arrival of information). However, the magnitude and persistence of the lead – lag relationship between returns and trading volume is so strong that the empirical are interesting independent of one's interpretation (Statman et al., 2006). For the other graphs of the impulse response function, see Appendix C.

4.4 Granger Causality for market returns and trading volume results

The granger causality test is conducted to address the second research objective. Granger causality test is conducted to detect the causality between returns and trading volume on GSE. However, this test is not conducted for such only purpose but also is conducted alongside the VAR model estimation in this study to check the validity of the results obtained from the VAR model. Employing 3 lags of the endogenous variables and 189 observations, the granger causality tests results is obtained (see Appendix D).

The null hypothesis that monthly trading volume does not granger-cause monthly market returns cannot be rejected since it has p-value more than .05 ($F - score = 1.20932$). Thus, the granger test reveals that trading volume has no significant impact on market returns. On the other hand, the second hypothesis that market returns do not granger cause trading volume is rejected at 5% level of significance ($F - score = 3.22166$). Thus, the rejection of the second null hypothesis implies that monthly returns granger-cause monthly trading volume. This shows that the monthly returns have impact on monthly trading volume. This implies that there exists unidirectional causality from monthly market returns to monthly trading volume on GSE. This result is in conformity with the VAR findings.

The unidirectional causality running from returns to trading volume is consistent with Tariq & Ullah (2013) findings of unidirectional causality running from market returns to trading volume on Pakistan stock markets. However, it is inconsistent with Metwally & Darwish (2013) who found bi-directional causality from returns and trading volume (using turnover as proxy) on Egypt stock markets.

The primary goal of this study is to test the rationality of market participants by investigating the evidence of overconfidence bias on Ghana stock market. Quite a number of interesting empirical evidence emerged from the data analysis. In general, the results above indicate that there is a significant association between past returns and current trading volumes on GSE. This empirical finding is confirmed by the VAR estimation, the impulse response function and the granger causality test. There is unidirectional causality running from market returns to market trading volume on GSE. It is also observed that market returns are autocorrelated which means investors can use past returns to predict future market returns. However, no significant contemporaneous nexus between trading volume and volatility on GSE is found as the literature postulates. Conversely, a negative significant contemporaneous relationship is recorded for trading volume and interest rate.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The study examined the rationality of market participants on GSE by using overconfidence bias of market players on Ghana stock market as a proxy. The aim of this chapter is to provide a summary of the previous chapters as well as to make recommendations to policy makers and future researchers.

5.2 Summary

The basic goal of this study is the testing of the rationality of investors on GSE. The goal was necessitated by vast empirical evidences of market inefficiencies and anomalies documented on GSE which deny GSE from the efficient allocation of resource benefits attributed to efficient capital market in the literature. Overconfidence bias as a behavioural bias is employed to test the rationality of market participants on GSE. The overconfidence bias of market participants have been investigated by numerous financial economists. According to Gervias & Odean (2001), due to the self-attribution bias, the overconfidence level of market agents is positively related to market return. Also, Odean (1998) reveals that overconfidence of market participants leads market participants to trade more. Based on these prior empirical studies, the lead-lag nexus between trading volume and returns is the framework adopted for this study following Statman et al. (2006).

Following Statman et al. (2006), a market-wide VAR model with monthly market trading volume and market returns as endogenous variables and volatility, interest rate and inflation as control variables is employed to examine the lead-lag between trading volume and returns on Ghana stock market. The study employed data from 2000 to 2015.

The empirical result indicates that previous market return is positively related to current market trading volume. A further analysis to ascertain the duration of the relationship is conducted by employing an impulse response function. The results from the IRF revealed that a shock to market returns residual result to approximately 0.12 and 0.19 rise in market trading volume at lag one and two respectively. However, the magnitude and persistence of the lead – lag relationship between returns and trading volume is so strong that the empirical are interesting independent of one's interpretation (Statman et al., 2006). As a result, this finding is an empirical evidence of overconfidence bias on GSE. This is consistent with overconfidence bias as explained by Statman et al. (2006). However, this overconfidence effect in the GSE market does not persist over a longer period as in the U.S. market. The granger causality test result revealed unidirectional causality from returns to trading volume. This also confirms the overconfidence bias since returns granger cause trading volume.

However, the positive contemporaneous nexus between trading volume and returns volatility documented in the literature, in line with Mixture of Distribution Hypothesis, is not evident on the Ghana stock market. Market returns is found to be autocorrelated but trading volume was not found to be autocorrelated. A cotemporaneous relationship between trading volume and interest rate is documented on GSE.

5.3 Conclusion

Consistent to expectation, the VAR model results indicate that past market return is related to current trading volume. The impulse response functions also show higher response of market trading volume to a shock of market returns residual. This implies that market participants on the Ghana stock market exhibit characteristics of overconfidence. Therefore, the market players on GSE exhibit conditional irrationality in the form of overconfidence bias. Also, a unidirectional causality from market returns to trading volume was documented. The researcher additionally introduced macroeconomic variables (inflation and interest rate) as a control variable in the VAR model, to capture the returns and macroeconomics variable relationship and the results is economically meaningful and as well as statistically significant for interest rate influencing trading volume in Ghana.

5.4 Recommendations

Based on these empirical results, the GSE regulators must appreciate the fact that the inefficiencies in the market may be as result of behavioural biases of market participants such as the overconfidence bias found in this study. The GSE regulators should consider behavioural biases as one of the possible cause of market inefficiency on GSE than arguing with the size of the market. The GSE regulators should come out with training programmes for market participants on behavioural biases and warn investors on existence of behavioural biases on the market so that they would not "confuse brains with a bull market" as the old Wall Street adage put it. Also, Ghana Stock Exchange Commission should incorporate behavioural finance in the programmes they run on the GSE to educate potential market participants on the presence of conditional irrational traders on the market.

Additionally, financial advisors, investment banks and brokers in Ghana should educate their clients about evidence of overconfidence behavioural bias on the exchange. They should educate them about the hazard of having behavioural biases such as overconfidence on their long run returns in the markets. If possible, they should conduct a study on their client to know which kind of behavioural biases they are exposed to so that they can advise accordingly.

Market participants should also note that whenever there is a positive market returns, the subsequent period trading volume will be high. Therefore, market participants can take advantage when designing their trading strategy in the GSE market where liquidity is a problem. Moreover, market participants should also not “confuse brains with a bull market” so that they can avoid this overconfidence bias which is reported in the literature to lead to low returns in the long run. Market participants should also understand that conditional irrational traders exist on the market and can cause deviations of stock prices.

Further studies should look at the overconfidence bias using individual market participant’s data on Ghana stock market. Future empirical research can also distinguish between individual and institutional investors to test the evidence of overconfidence bias for these classes of investors. Similarly, it is recommended that other studies also consider other behavioural biases documented in the literature such as disposition effect on GSE.

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APPENDICES

Appendix A: Unit root test for stationarity

Time series	ADF			PP			KPSS	
	Intercept	Trend and intercept	None	Intercept	Trend and intercept	None	Intercept	Trend and intercept
MLTVOL	−3.837366	−11.09054	0.288492	−8.745951	−11.34236	0.513044	1.409623	0.146152
MDLTVOL	−12.49416	−12.46239	−12.16233	−12.13247	−12.10849	−12.16233	0.031042	0.031042
MRET	−4.011922	−7.908808	−3.780846	−8.195103	−8.190272	−7.967643	0.150388	0.051700
MSIG	−9.445207	−9.472464	−8.062961	−9.431641	−9.456400	−8.386833	0.119673	0.078558
LCPI	−2.278699	−1.776909	0.399669	−2.357827	−2.017417	0.419590	0.889976	0.328708
ΔLCPI	−18.88646	−18.99190	−18.90307	−19.63197	−19.60074	−19.52352	0.250890	0.038807
LTBR	−2.231441	−1.867767	−0.571958	−1.987544	−1.813355	−0.537103	0.404497	0.278319
ΔLTBR	−8.100429	−8.123632	−8.115774	−8.361481	−8.380459	−8.376260	0.121375	0.043171
Lag length	14	14	14					

Note: ***,** and * indicates significant at 1%, 5% and 10% level respectively ADF = Augmented Dickey-Fuller (1997) Test; PP = Phillips-Perron (1988) Test; KPSS = Kwiatkowski, Phillips, Schmidt, And Shin (1992) Test

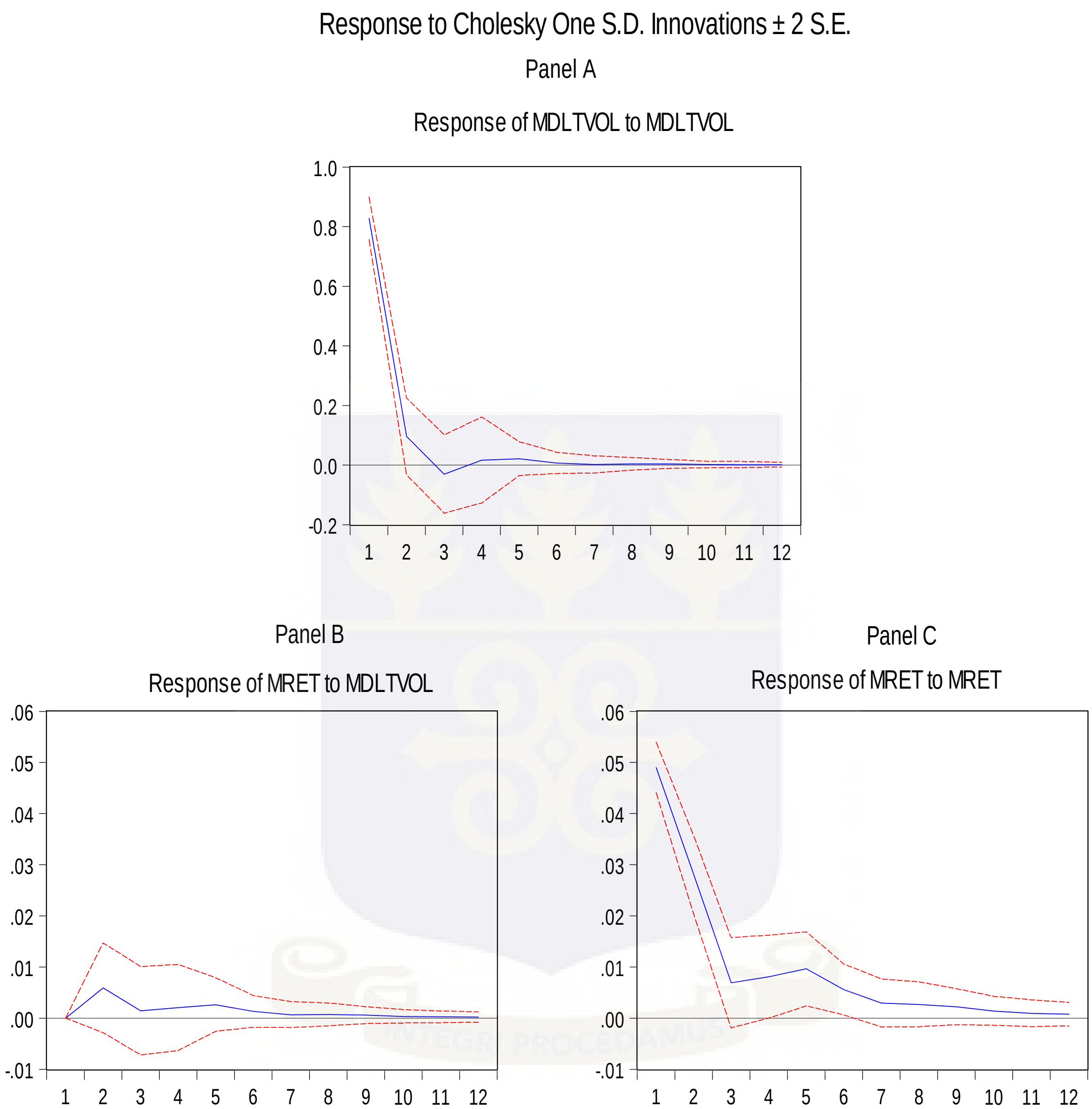
Appendix B: Residual Portmanteau VAR tests for Autocorrelations

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: no residual autocorrelations up to lag h

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.192324	NA*	0.193364	NA*	NA*
2	1.378357	NA*	1.392288	NA*	NA*
3	2.712487	NA*	2.748289	NA*	NA*
4	7.596342	0.1075	7.739482	0.1016	4
5	9.894491	0.2725	10.10112	0.2580	8
6	10.59409	0.5640	10.82403	0.5441	12
7	13.72015	0.6196	14.07235	0.5933	16
8	25.75831	0.1739	26.65154	0.1454	20
9	25.90585	0.3580	26.80659	0.3135	24
10	28.00334	0.4643	29.02325	0.4113	28
11	32.78800	0.4282	34.10867	0.3665	32
12	36.41691	0.4493	37.98784	0.3789	36
13	38.57358	0.5345	40.30657	0.4567	40
14	46.94196	0.3528	49.35610	0.2677	44
15	50.68471	0.3681	53.42716	0.2737	48
16	56.25098	0.3188	59.51731	0.2209	52
17	58.08464	0.3984	61.53542	0.2846	56
18	60.35956	0.4627	64.05408	0.3363	60
19	68.42211	0.3297	73.03393	0.2055	64
20	70.08058	0.4076	74.89221	0.2647	68
21	79.82521	0.2467	85.87708	0.1263	72
22	82.48333	0.2859	88.89178	0.1480	76
23	84.08806	0.3556	90.72294	0.1936	80
24	84.38716	0.4676	91.06635	0.2804	84
25	86.29376	0.5315	93.26900	0.3301	88
26	91.26422	0.5021	99.04716	0.2892	92
27	94.68894	0.5187	103.0534	0.2929	96
28	98.92050	0.5117	108.0349	0.2741	100
29	99.80070	0.5982	109.0777	0.3473	104
30	102.5998	0.6286	112.4150	0.3663	108

*The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution
*df and Prob. may not be valid for models with exogenous variables

Appendix C: Impulse Response Function of the VAR model



Appendix D: Pairwise Granger Causality tests for Returns and Volume (Lags: 3)

Null Hypothesis:	Obs	F-Statistic	Prob.
MDTVOL does not Granger Cause MRET	189	1.20932	0.3078
MRET does not Granger Cause MDTVOL		3.22166	0.0239