CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the University of Dar es Salaam a dissertation entitled: ***Testing behavioural finance theories on a frontier market- the case of Nairobi Securities Exchange***, in partial fulfilment of the requirements for the degree of Doctor of Philosophy (Economics) of the University of Dar es Salaam.

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DECLARATION AND COPYRIGHT

I, Patrick Olowo, declare that this dissertation is my own original work and that it has not been presented and will not be presented to any other University for a similar or any other degree award.

Signature: ....

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DEDICATION

To

Nata- *Nataanywaki*

ABSTRACT

This study investigates whether the revision of the NSE-20 share index yields abnormal returns and also if psychology (overconfidence) influences investment decisions at the NSE as is predicted by behavioural finance. On the one hand, wanting to exploit abnormal returns that are likely to result from the revision of the NSE-20 share index could be costly due to the involved costs and risks (limits-to-arbitrage argument). On the other hand, the expanding trading volume at the NSE over time could signal excessive trading that translates into loss in wealth for those engaged in it as is predicted by the overconfidence bias. We employ financial time econometrics to achieve our objectives.

The study's findings indicate that while the periodic revision of the NSE-20 share index yields abnormal returns, they are not statistically significant. Further, investment decisions depict psychological biases of overconfidence and its dynamic counterpart; biased self-attribution. Unlike in developed markets where the level of overconfidence depends on the precision of investor forecasts, in frontier markets overconfidence is high even when forecasts are highly imprecise. In addition to other factors, over-confidence-based trading contributes to excess volatility in the market. The study recommends that Kenya's financial consumer protection programme that deals with financial regulation and financial literacy should be behavioural finance-biased since there is evidence that behavioural biases are at play in this market. It is expected that well informed and psychologically astute investors can better their capital allocation decisions.

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LIST OF ACRONYMS AND ABBREVIATIONS

NSE	Nairobi Securities Exchange
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
EGARCH	Exponential Generalised Autoregressive Conditional Heteroskedasticity
GJR-GARCH	Glosten Jagannathan and Runkle GARCH
EMH	Efficient Markets Hypothesis
PPH	Price Pressure Hypothesis
ISH	Imperfect Substitutes Hypothesis
DSDC	Downward sloping Demand Curve Hypothesis
LCH	Liquidity Cost Hypothesis
ICH	Information Content Hypothesis
OLS	Ordinary Least Squares
ADF	Augmented Dickey Fuller test
KPSS	Kwiatkowski Phillips Schmidt and Shin test
IAH	Investor Awareness Hypothesis

CHAPTER ONE

INTRODUCTION

1.1 Introduction to the study

Traditional or orthodox finance paradigms have Fama's (1970) Efficient Markets Hypothesis (EMH) as the tool of financial markets analysis. The EMH serves as the foundation for financial asset pricing as well as the basis for explaining and predicting the behaviour of investors and other players in the market. It is premised on the rationality of the economic agents as well as frictionless markets in which security prices reflect only the fundamental value of the securities. In an efficient market, therefore, there is "no free lunch". No investment strategy can earn excess risk-adjusted returns (Barberis and Thaler, 2003). Within the EMH framework, one cannot predict stock prices or their future trend in any way (Stangle *et al*., 2005) and besides investors are rational agents.

The challenge that faces such orthodox finance is the emergence of market phenomena that are not compatible with the EMH predictions. Such observations include but are not limited to- overreaction to news surprises that affect stock price level (De Bondt and Thaler, 1985, 1987); occurrence of significant abnormal returns on index revision dates and immediately afterwards (Harris and Gurel, 1986; and Shelifer, 1986). Also, there is occurrence of high trading volume in stock markets than is implied by the EMH (De Long *et al*., 1990; Kyle and Wang, 1997; Wang, 1998, 2001; and Gervais and Odean, 2001). The first two examples depict inefficiencies in markets where as the last one depicts human biases inherent in investor decisions.

Index revisions, that is efforts to ensure that a given index remains representative of a given market often result in increased (decreased) returns for the included (excluded) stocks. In other words, index revisions could exert lasting or temporary effects on the prices of the affected stocks even when the revision does not affect the fundamentals of the firm (Harris and Gurel, 1986; and Shleifer, 1986). The investors may fail to exploit the resulting abnormal returns due to constraints (risks and costs) technically referred to in behavioural finance literature as the limits-to-arbitrage. The continued presence of a profitable unexploited mispricing in the market violates the EMH.

Further, the observed anomaly of high trading volumes in markets is attributed to a psychological bias of overconfidence that is inherent in individual and institutional investors across markets (Barberis and Thaler, 2003). The overconfidence bias describes the human tendency of overestimating one's ability in performing certain tasks. It shows that individuals seem to believe that they know more than they actually do know (Kahneman, 2011) In essence the overconfidence bias breeds excessive trading in markets because individuals think that they have information that is strong enough to justify a trade whereas in fact the information they possess is too weak to warrant any action. If rationality were common knowledge to all agents as is stressed in orthodox finance, one party would be reluctant to buy if the other were to sell. Consequently, very little or no trading would be taking place but this is not the case as there are high levels of trading volume across markets. The combination of inefficient outcomes following index revisions on the one hand and the existence of inherent psychological biases in investor decisions on the other are likely to lead to sub-optimal resource allocation outcomes. Investors could lose resources in a bid to exploit the seemingly likely profit opportunity that arises when a given stock is added to the market index. Equally, psychological biases such as overconfidence and self-attribution bias generate unnecessary trading in the market. Consequently, overconfident investors trade more frequently and fare worse than those who trade less (their wealth declines); they hold under diversified and riskier portfolios though they have the same degree of risk aversion (Odean, 1999). The study by Barber and Odean (2001) shows men to be more overconfident than women thereby trading more frequently and ultimately earning less than their female counterparts who trade less frequently in the United States (US).

Behavioural finance[1] is a new approach to financial markets that has emerged, at least in part, in response to the difficulties faced by the traditional finance paradigms in explaining some market phenomena that violate the EMH (Barberis and Thaler, 2003). It is developed around two pillars that is the limits-to-arbitrage and psychology. The gist of the limits to arbitrage is that rational investors faced with high costs and risks may not necessarily correct the deviation of security prices from their fundamental value where as psychology outlines human sentiment which underlie the decision-making processes of investors and other parties in the market. Olsen (1998) argues that in the behavioural finance setting, it is possible to study various market phenomena by examining the interaction of psychological biases and financial market activity, which is not the case in the traditional finance framework.

[1] It is also referred to in the literature as market inefficiency theories and an alternative to the EMH (Chan *et al.*, 2004)

Empirically, behavioural finance hypotheses are found to hold in developed stock markets in the US, Europe, Japan and in some emerging economies like China and some Asian Pacific economies (Chuang and Lee, 2006; Kim and Nofsinger, 2007; Li and Sadeghi, 2009). Although stock markets world over play similar roles, their classifications into different categories implies existence of significant differences[2] between them. Consequently, it would be reasonable for one to suspect *apriori* that the differences in the market settings would yield different outcomes.

The classification of markets as developed, emerging or frontier status is determined by the compilers of global market indices based on an assessment of the nature and sophistication of the stock market in relation to the degree of development of the economy, (S&P, 2007; Nellor, 2008). In the year 2000, Standard & Poor's (S&P) - a highly reputable International Credit Rating Agency took over the compilation of the emerging market financial indices from the International Finance Corporation (IFC) - a private sector arm of the World Bank Group. They used the term frontier markets to describe countries with markets that are smaller and less liquid than those in more advanced emerging markets. The S&P frontier market indices include various markets in developing countries including Kenya's Nairobi Securities Exchange (S&P, 2007).

Another compiler of global market indices the Financial Times and London Stock Exchange (FTSE) Group classifies markets as developed, advanced emerging, secondary emerging and

[2] We show these differences in terms of the criteria used in classifying markets by the FTSE Group in Appendix Table 1.1.

frontier (FTSE, 2010). The criteria used to categorise countries follow a wide range of aspects that include the World Bank's Gross National Income (GNI) per capita rankings, the markets' infrastructure such as the regulatory environment, the settlement systems, presence of derivative markets and size of markets (see Appendix Table 1.1).In both developed and frontier stock markets there is strict regulation by the relevant authorities, foreign investor participation, a reasonably shorter trade cycle as well as timely reporting of trade deals.

Nevertheless there are recognisable differences between developed and frontier markets that necessitate the examination of both markets independently of each other. Specifically, in developed markets, equities and foreign exchange markets are highly advanced unlike in frontier markets. Besides, minority share holders in developed markets are fairly protected as compared with frontier markets. Additionally, the developed world offers a relatively easier participation in its markets to foreigners than the developing world.

Further differences exist in the length of settling and clearing of deals- it takes a shorter period in developed markets to clear a deal than in a frontier market. There is sufficient broad market liquidity to support sizeable global investment in developed markets unlike in frontier ones. More to that developed markets permit off-exchange transactions and their trading mechanisms are efficient where as such arrangements are not available in frontier markets.

The services that are at the disposal of developed market participants are unavailable in frontier markets. Specifically, derivative markets are well developed; stock lending that can enable margin trading is feasible, possibilities of short selling as well as availability of developed and competitive brokerage services. The availability of such services is a pointer to the high level of sophistication and the liquidity of the markets.

With all the advancement and sophistication developed markets, individual and institutional traders depict psychological biases that lead them in taking positions that are not rational and there by lose resources. The pronounced differences between the market features of developed and frontier markets means that applying the empirical conclusions of behavioural finance from the former over the latter may seem unreasonable. There is need to establish how behavioural finance predictions fare in a representative frontier market in order to inform policy formulation. This study's choice of East and Central Africa's largest and oldest securities exchange –the NSE- is due to the fact that it is the only regional market that passes the classification criteria as a frontier exchange. We therefore examine its various features in relation to behavioural finance predictions.

1.2 The Nairobi Securities Exchange (NSE)[3]

As of December 31, 2010, East and Central Africa's oldest and most vibrant securities exchange, the NSE, had the following registered securities: 55 equities[4], 11 corporate bonds

[3] For the historical evolution of the NSE please refer to Ngugi (2003a)

[4] The list of the 55 equities is indicated in Appendix Table 1.2 This list does not indicate the Fixed Income Securities Market Segment because this segment is indicative of preference shares offered by firms already indicated in other segments.

and over 60 government bonds. As a way of attracting firms of varied capital bases, the NSE devised a three-market segmentation to categorise the listed securities. The Main Investments Market Segment (MIMS), the Alternative Investments Market Segment (AIMS) and the Fixed Income Securities Market Segment (FISMS) are the categories where securities fall. The basis for this segmentation is to improve the level of market access to all investors with each market segment catering for the varied investment needs and risk profiles of the investors (NSE, 2002). Trading on the exchange takes place daily from Monday to Friday at 09:00 hours to 15:00 hours.

The market has two major indices; the NSE-20 share index and the NSE All Share Index (NASI) that was launched in February 2008. The former is computed as a geometric mean of 20 prices of selected securities hence it is an equal-weighted index where as the latter's computation is based on market capitalisation so as to reflect the total market value of the constituent stocks. Two other complementary indices were launched by the NSE and the FTSE Group on November 8, 2011; these are the FTSE NSE Kenya 15 and the FTSE NSE Kenya 25 indices (NSE, 2012).

The launching of these two latest indices that is intended to enhance and capture the depth of information available on the Kenyan securities market globally, marks a significant milestone in the development of this market (NSE, 2012). It is anticipated that the branded indices will improve capital flows into the domestic market, enhance liquidity and market capitalisation.

The main market index is still the NSE-20 share index where as the NASI complements it. The securities included in the NSE 20-share index are on average the most dominant gauging by the size of their market capitalisations as depicted in Table 1.1.

Table 1.1: NSE-20 Share Index Constituents as at August 31, 2010

	Price (Ksh)	Shares Outstanding (M)	Market Capitalisation (Ksh.bn)	% Mkt cap
Safaricom Ltd	4.85	40,000	194.00	17.08
East African Breweries Ltd	179.00	791	141.55	12.46
Equity Bank Ltd	25.00	3,703	92.57	8.15
Barclays Bank Ltd	65.50	1,358	88.94	7.83
Bamburi Cement Ltd	201.00	363	72.95	6.42
Standard Chartered Bank Ltd	251.00	272	68.26	6.01

The Co-operative Bank of Kenya Ltd	16.50	3,492	57.62	5.07
Kenya Commercial Bank Ltd	19.00	2,218	42.14	3.71
KenGen Ltd.	17.45	2,198	38.36	3.38
British American Tobacco Kenya Ltd	261.00	100	26.10	2.30
Nation Media Group	158.00	143	22.53	1.98
Kenya Airways Ltd	47.00	462	21.70	1.91
Mumias Sugar Co. Ltd	11.75	1,530	17.98	1.58
Kenya Power & Lighting Ltd	206.00	79	16.30	1.43
Athi River Mining	162.00	99	16.05	1.41
CMC Holdings Ltd	13.00	583	7.58	0.67
E.A.Cables Ltd	18.85	203	3.82	0.34
Sasini Ltd	13.25	228	3.02	0.27
Rea Vipingo Plantations Ltd	18.00	60	1.08	0.10
Express Ltd	9.90	35	0.35	0.03
Aggregate Mkt Cap for the NSE-20 firms (bn)			**932.90**	**82.12**
Total Market Capitalisation (bn)			**1,136.07**	

Source: NSE Daily Price List 31/08/2010

Table 1.1 depicts the NSE-20 share index constituent firms as at the end of August 2010. It is evident that 82% of the total market capitalisation is attributed to the NSE-20 share constituent firms. Firms with the highest capitalisation levels are Safaricom Ltd, East African Breweries Ltd, Equity Bank Ltd, Barclays Bank Ltd and Bamburi cement Ltd where as Sasini Ltd, Rea Vipingo Plantations Ltd and Express Ltd have the lowest capitalisation levels. The NSE-20 share index constituent firms' revision takes place periodically such that the main market index remains a true barometer of the NSE (NSE, 2010).

In light of the best international practice, the exchange publicly avails information on the criteria for inclusion of stocks in the main market index to all market participants. The largest 20 securities valued by full market capitalisation and satisfying all investibility screens by the exchange are eligible for inclusion (NSE, 2007). The NSE rules on inclusion stipulate that for a company to qualify it must meet the following requirements: its shares must have their primary listing on the NSE; and it must have at least 20% of its shares quoted on the NSE. Additionally, a company must have been continuously quoted for at least 1 year with a minimum market capitalisation of Kenya Shillings 20 million; and should ideally be a blue chip (have superior profitability and dividends record).

The fact that the criteria of inclusion into and exclusion from the NSE-20 share are within the public domain, finance theory predicts that such events would not affect share prices or bring about significant abnormal returns. This would be the case because releasing information about an impending index revision or effecting a change does not constitute any new information that can affect the market because the criteria is known by all. However, some empirical studies from several developed markets indicate significant abnormal returns following index changes (Harris and Gurel, 1986; Shleifer, 1986; Woolridge and Ghosh, 1986; Dhillon and Johnson, 1991; Yun and Kim, 2010; Liu, 2011).

The investor profile of the NSE indicates that the majority of the participants in terms of total equity held are institutional investors (CMA, 2010). Table 1.2 indicates that local corporate bodies, followed by local individual investors hold the highest percentage of equity shares (that is 42% and 34% respectively) whereas foreign corporate bodies hold a sizeable amount of 19.7%. Individual foreign investors and East African individuals (nationals) hold the least percentage of share equities.

Table 1 2: Investor profiles at the NSE as at March 31, 2010

	Category of Investors	No. of Investors	No. of Shares	% of shares (equities) held
1	Foreign Individuals	3,863	225,514,295	1.16
2	East African Corporate	242	494,869,948	2.54
3	East African Individuals	6,265	229,629,348	1.18
4	Local Corporate	41,518	8,121,812,870	41.64
5	Local Individual	899,497	6,590,936,650	33.79
6	Foreign Corporate	218	3,843,309,511	19.7

Source: CMA, 2010

The size of licensed institutions that deal in the trading of equity and other financial assets is quite reasonable. Specifically there are 11 licensed stock brokers, 10 investment banks, 19 investment advisors and 21 fund managers (CMA, 2012). Since there are no licensed dealers currently, this could affect the exchange's liquidity levels. The criteria of classifying of stock markets to different classes entail an examination of the level of competition in the brokerage industry (see Appendix Table 1.1). A highly competitive brokerage industry is expected to bring about quality services to the investing public.

Kenya and all the other countries such as Botswana, Ivory Coast, Mauritius, Nigeria, Tunisia and Ghana that fall in the category of frontier markets[5] pass the test of having quality and competitive brokerage services (see Appendix Table 1.3). Kenya's security exchange does not meet a number of aspects a developed market must have. Specifically, its equities and

[5] The stock market in the Republic of South Africa is categorised as advanced emerging whereas Egypt's and Morocco's are secondary emerging. All these have better structures than the frontier markets. A point to note though is that the other regional stock markets in Uganda, Tanzania, Rwanda, Malawi and Zambia do not make the categories.

foreign exchange markets are not fully developed; it does not permit stock lending and short sales, has no derivatives market and lacks sufficient liquidity to support sizeable global investment (see Appendix Table 1.3).

Table 1.3 summarises the key gross market statistics of the NSE. The key measures of trading activity are the share volume and share turnover which give an indication of the trends in the amount and value of shares traded respectively. It is evident that in the early 1990s the volume of shares traded is lower relative to that of the mid to the late 1990s. The share turnover depicts mixed results of upward and downward movements in the period of 1994 to 2002. The overall market trading activity shows an upward trade from 2003 onwards.

Similarly, market capitalisation trends do not differ much from those of traded volumes. Specifically, market capitalisation is much lower in the early 1990s but it shows a consistent upward movement from the year 2002 onwards. The NSE-20 share index shows a sharp increase in the first three years that is followed by a continuous decline for the next nine consecutive years. From the year 2003, the index depicts a consistent continuous increase.

Table 1.3: NSE Key Market Statistics

Years	Share Volume (Million)	Share Turnover (Billion)	Market Capitalisation (Kshs. Bn)	NSE-20 share Index
1991	16.6	0.3	12.71	958
1992	14.8	0.38	23	1,167
1993	27.3	0.82	72	2,514
1994	42.76	3.08	136.83	4,559
1995	62.1	3.34	107.2	3,469

1996	113.6	3.96	98.68	3,114
1997	143.47	6.15	114.31	3,115
1998	111.11	4.58	128.94	2,962
1999	157.49	5.16	106.74	2,303
2000	141.42	3.63	101.42	1,913
2001	109.19	3.12	86.1	1,355
2002	106.07	2.02	83.3	1,087
2003	198.1	7.51	180.65	1,935
2004	525.88	20.35	274.41	2,640
2005	579.94	22.03	420.7	3,972
2006	1,227.82	60.28	623.2	4,260
2007	1,497.55	100.32	745.9	5,146
2008	2,154.90	106.84	853.7	5,185

Source: CMA, 2000, 2002 and 2008

Notes: The figures quoted correspond to the last date of each calendar year.

The graphical presentations in Figures 1.1, 1.2 and 1.3 support the tabulated key NSE market statistics. It is evident from the graphs that the volume, the NSE-20 share index and the market capitalisation values are low for most of the 1990s. The three statistics show an upward trend from the year 2003 onwards. One intuitive interpretation of this trend is that the amount of shares traded on the market has been increasing over the years and so has been the wealth created.

Figure 1.1: Trends in volume of shares traded at the NSE

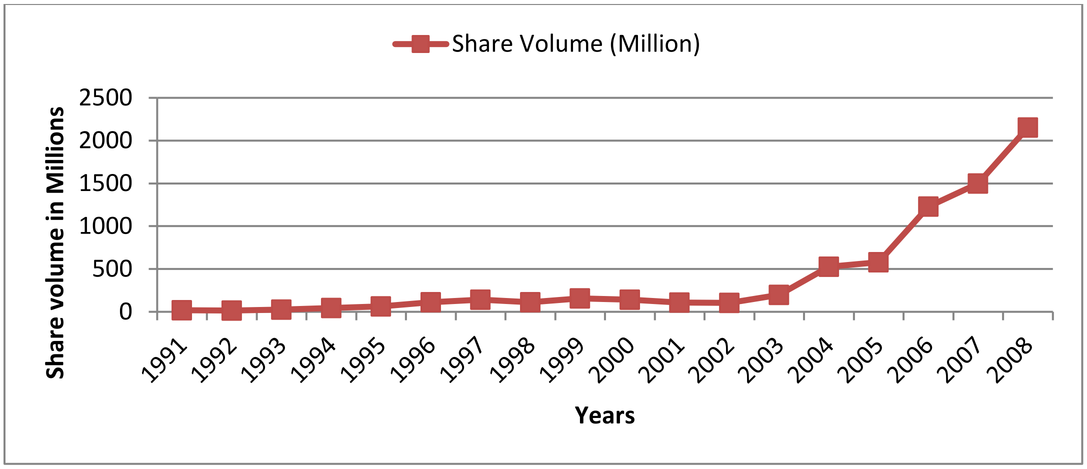


Figure 1.2: Trends in the NSE-20 Share Index

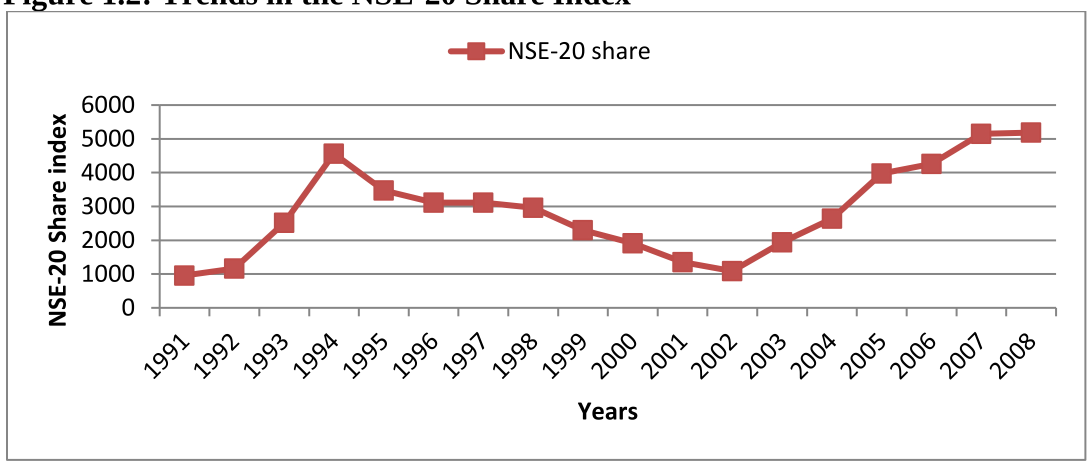
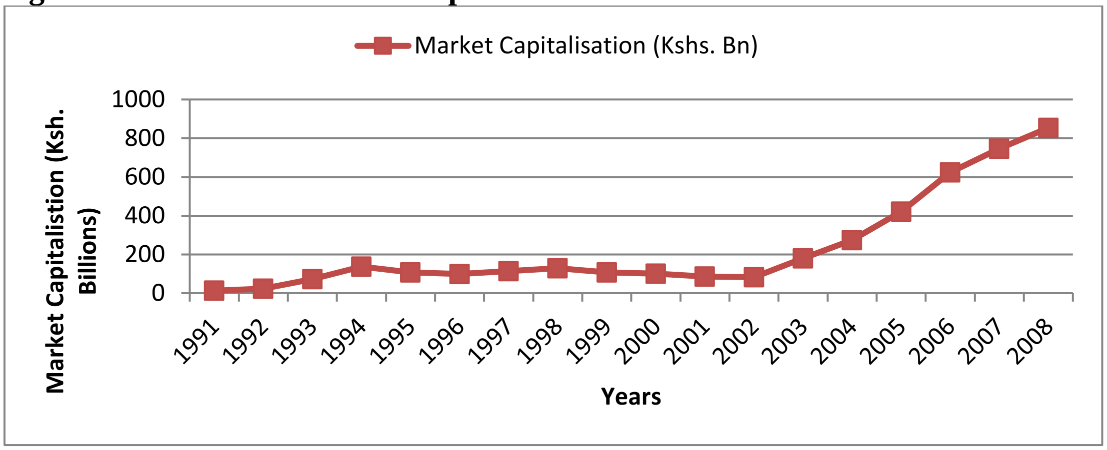


Figure 1.3: Trends in Market Capitalisation at the NSE



Of particular interest to this study is the examination of the trading volume of the NSE for it (trading volume) contains information on how security prices evolve over time and it's a pointer to investor sentiment in any market (Lei, 2005). One form of sentiment that affects investor trading is that of overconfidence and its key side effect is increased trading volume.

Waweru *et al*. (2008) suggest three indicators of how investors (institutional and individual) at the NSE choose stocks for their portfolios; these are the daily abnormal trading volumes, daily returns and daily news. Since investors at the NSE follow daily trading volume to choose their portfolios, an examination of the trading volume behaviour for psychological biases such as overconfidence is crucial to this study. We build on the Waweru *et al*. (2008) suggestion above to investigate the trading volume of the NSE whether it contains any element of sentiment as suggested by behavioural finance theories.

Further, the observation that investors at the NSE choose their stocks by examining daily stock returns and daily news means that the NSE-20 share index which is the main market index is widely followed. Since it is a price-weighted index it basically contains news relating to the equally weighted price movements of 20 of the largest companies (blue chip stocks) listed on the NSE. Any revisions of this index (which the NSE does anyway) would interest the investors since empirical finance shows that significant abnormal returns could result.

The period 2003 to 2010 indicates that the NSE-20 share index was revised 5 times. In the event that there are observable significant abnormal returns following the revision of the NSE-20 share index, behavioural finance theorists would argue that traditional finance's belief in the EMH fails to hold in the weak-form sense. They would therefore provide an alternative explanation of existence of limits-to-arbitrage theory that constitutes one of the pillars of behavioural finance.

Empirical evidence in Waweru *et al*. (2008) suggests that behavioural biases alluded to in the behavioural finance school is inherent in the investment decisions of the institutional investors operating on the NSE. Besides, personal finance decisions also carry with them psychological biases that lead to predictable but sub-optimal decisions (De Meza *et al*., 2008).It is partly due to the biases in the investors' decisions in capital markets that the case for financial consumer protection is made stronger.

Financial consumer protection is delivered in two ways; namely, financial regulation and financial education/literacy programmes (Rutledge *et al*., 2012). Behavioural finance identifies a host of systematic biases many of which are evident in investment decisions that individuals make. Behavioural finance theorists suggest that in designing financial consumer protection programmes, the focus should be on exposing the potent biases, introduce regulations that recognise their presence and offset their effects in the least intrusive fashion possible (De Meza *et al*., 2008 and Thaler and Sustein, 2009).

In testing behavioural finance theories on the NSE, this study builds on Waweru *et al*. (2008) findings that institutional investors exhibit psychological biases in their investment decisions. However, the conclusions from their study are based on a small sample of 23 institutional investors and more fundamentally on the survey data approach that reflects the perceptions of the respondents. An improved and feasible approach that the current study employs is the time series approach that examines secondary market-level data of the NSE. This kind of data captures the actual actions (outcomes) of all the investors, both institutional and individual. Additionally, other than relying on market surveys that indicate perceptions of the investors which might differ from their actions, the current study employs market-level data that indicate investor action.

1.3 Statement of the Problem

Empirical evidence in Harris and Gurel (1986) and Shleifer (1986) indicates the occurrence of significant abnormal returns following index revisions- a result that is unpalatable with the EMH predictions. Should significant abnormal returns arise in any NSE-20 share index revision event, behavioural finance theorists would argue that any attempts to exploit them would be costly to investors due to the nature of high risks and costs implied in the limits-to-arbitrage.

Further, trading volume at the NSE has shown an upward trend for most of the last decade. Trading volume contains traceable behavioural biases that are inherent in investor decision-making. One such bias is overconfidence- the tendency to overestimate the precision of one's own private information signals when deciding on which stocks to invest in. The immediate outcome of such a bias is excessive trading that reduces the wealth of those that engage in it (Odean, 1999; and Gervais and Odean, 2001) and increased volatility.

The challenge facing the investors is that Kenya falls short in providing a comprehensive financial consumer protection programme that would mitigate some of the dangers of behavioural biases (Flaming *et al.*, 2011). A combination of financial regulation with financial literacy programmes would constitute a comprehensive financial consumer protection scheme. The Capital Markets Authority of Kenya (CMA) that deals with the regulation of the NSE also provides investor education and promotes public awareness in capital markets in Kenya. An empirical examination of behavioural finance theories illuminates the psychological biases at the NSE. It is anticipated that educated and psychologically-astute investors should be able to better their capital allocation decisions.

1.4 Objectives of the study

The broad objective of this study is to test behavioural finance theories on a frontier securities exchange such as the NSE. Specific objectives of this study include the following:

i) Testing the overconfidence hypothesis on the NSE data, and

ii) To test for the effects of index revisions on the share prices of the affected stocks.

1.5 Justification of the study

The justification of this study is three-fold; methodological, empirical evidence and policy relevance.

The adopted methodology in this study can be categorised into two- traditional financial time series using aggregate market data and the event study methodology. Time series procedures based on aggregate market level are premised on Odean (1998b) and Gervais and Odean (2001) that investor behaviour is observable in market level data. The only available study by Waweru *et al*. (2008) of behavioural finance on the NSE employs survey methods that involve a small number of institutional investors. The use of time series econometric techniques enables us to study the fundamental statistics of trading volume, market returns and stock returns of the NSE that are rather difficult to capture in survey methods.

The event study methodology allows us to observe the impact of various events on security prices using a relatively short period. Since there is a problem of thin trading at the NSE (Dickinson and Muragu, 1994), it is possible to control for it when studying index revisions within the event study methodology. Apart from studies from developed markets, this kind of methodology has not been employed in studying index revisions at the NSE.

On the empirical front, we distinguish this study from similar ones in behavioural finance in the sense that most research in this area concentrates on the developed financial markets of the US, Western Europe and Japan and in some cases on the emerging markets in the Asia pacific region. For example the overconfidence hypothesis in, Kyle and Wang, 1997; Odean, 1998a; Hirshleifer and Luo, 2001; and Chuang and Lee, (2006) concentrates on US markets. The limits-to-arbitrage theory in Shleifer and Vishny, (1997) is empirically proven in forms of mispricings found in developed markets. The variation in the structure of frontier markets and developed markets is likely to yield different results and conclusions. This is so because frontier markets like NSE, have limited stocks, lower market capitalisation levels, experience infrequent trading, and less efficient trading mechanisms with no derivative markets and no short sales permitted (see Appendix Table 1.3).

The policy- relevance- justification for a behavioural finance study on the NSE lies in the fact that the market is not highly sophisticated by international standards neither are all its participants. The knowledge of the interaction between psychological biases and investment decision-making inherent among individual investors, institutional investors, investment analysts and asset managers can help the market regulators to take appropriate action to improve market out comes through a well-designed financial consumer protection programme.

1.6 Organisation of the study

This study has five chapters of which chapter one covers the introduction to the study, and chapter two covers both theoretical and empirical literature. Chapter three lays down the empirical methodologies underlying the two specific objectives of testing for overconfidence and index inclusions. Chapter four provides the results and their discussion whereas chapter five contains the overall conclusions and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, we lay out the theoretical and empirical behavioural finance literature. To articulate the behavioural finance theories, we first review key traditional finance paradigms. The behavioural finance literature that we present broadly follows the two pillars of behavioural finance that is, the limits-to-arbitrage theory and psychology.

2.2 Theoretical literature

2.2.1 Traditional Finance and the EMH

There are two central assumptions underlying the traditional finance paradigms that is, the agents' rationality and the law of one price (Glaser *et al*., 2003). The rationality of the economic agents translates into two things. First, when they receive new information, agents update their beliefs correctly, in the manner described by Bayes' law (Barberis and Thaler, 2003 pp.1053). What this means is that in the process of updating their beliefs, agents are able to weigh potential future outcomes using probabilities that reflect the frequencies with which these will factually occur. In other words, their priors coincide with the true probability measure. The agents, therefore, correctly infer the necessary information from signals (including prices from the market) and apply the rules of conditional probability (Bayes' law) to update their beliefs (Bondarenko and Bossaerts, 2000).

Second, given their beliefs, agents make choices that are normatively acceptable, in the sense that they are consistent with Savage's notion of Subjective Expected Utility (SEU) (Barberis and Thaler, 2003). In a world that is full of uncertainties individuals or investors face a number of choice options, which Savage depicts in a preference relation formulation (Shafer, 1986). In evaluating these choice options, the agents consider their own tastes as well as their beliefs regarding their realisation. Given a set of axioms, individual preferences regarding choice options can be ranked and therefore Savage asserts that all rational individuals' preferences agree with a ranking by subjective expected utility (Shafer, 1986). Hence, individuals make choice options that maximise subjective expected utility and to do otherwise one violates the cannons of rationality.

The other central assumption of traditional finance, at least from a market perspective, is the law of one price. This states that securities with the same payoff have the same price (Glaser *et al*. 2003). Arbitrageurs eliminate instantaneously any violations of the law of one price by simultaneously buying and selling these securities at advantageously different prices. Consider, for example, the shares of East African Breweries Limited (EABL) whose trade occurs simultaneously on both the Nairobi Securities Exchange (NSE) and on the Uganda Securities Exchange (USE) during the same trading hours. If one takes adjustments in the current Kenya shilling – Uganda shilling exchange rate, the EABL shares should be priced the same on both exchanges. If the adjusted prices were different from each other, an arbitrageur would sell shares at the higher price at one exchange, would buy the same number of shares at the other exchange with lower prices, and would thus realise a risk-less profit (Glaser *et al*., 2003).

Traditional finance reflects the body of knowledge built on the pillars of arbitrage principles of Miller and Modigliani, the portfolio principles of Markowitz, the capital asset pricing theory of Sharpe, Lintner and Black and the option-pricing theory of Black, Scholes and Merton (Statman, 1999). The driving force of all these economic ideas is the assumption of rationality, which ensures that agents/investors always make the right decisions using the available complete information and succeeding in achieving to optimise the intended benefits (Hubert, 2001; Subrahmanyam, 2007). It is not surprising therefore for the traditional finance school to hypothesise about market efficiency in the Efficient Market Hypothesis (EMH) sense.

Fama (1970) defines an efficient market as one where prices always fully reflect available information. Different forms of market efficiency exist due to the amount of information that is assumed available. If the current price contains only the information consisting of past (historical) prices, the market is said to be weak-form efficient. If prices reflect all publicly available information such as historical prices, earnings announcements, stock splits and the like, the market is semi-strong form efficient. Finally, if prices reflect all information including private information, the market is strong-form efficient.

One can therefore assert that the EMH represents the set of hypotheses that express the intuition that the information held by market participants is depicted in the asset prices. To make excess risk-adjusted returns is rather difficult in an efficient market hence all trading schemes based on the same information that is already embodied in the prices including all publicly available information, are bound to fail.

From a theoretical point of view, the proponents of the traditional finance paradigms assert that in an efficient market one cannot beat the market by examining the patterns of security prices. They argue that tests for market efficiency should always be a joint test of market efficiency and the assumed correctness of a well-specified capital asset pricing model (Statman, 1999; Glaser *et al*., 2003). However, a number of market outcomes[6] are incompatible with market efficiency even after adopting a well-specified capital asset pricing model. The resultant question is whether such market outcomes signal real profit opportunities and thus a violation of market efficiency or just a proper reward for risk.

2.2.2 Introduction to behavioural Finance

Behavioural finance is a sub discipline of behavioural economics. It is finance that incorporates findings from psychology and sociology into its theories. Statman (1999) argues that much as some people think that behavioural finance introduced psychology into finance, psychology had never been out of finance. From the perspective of financial markets

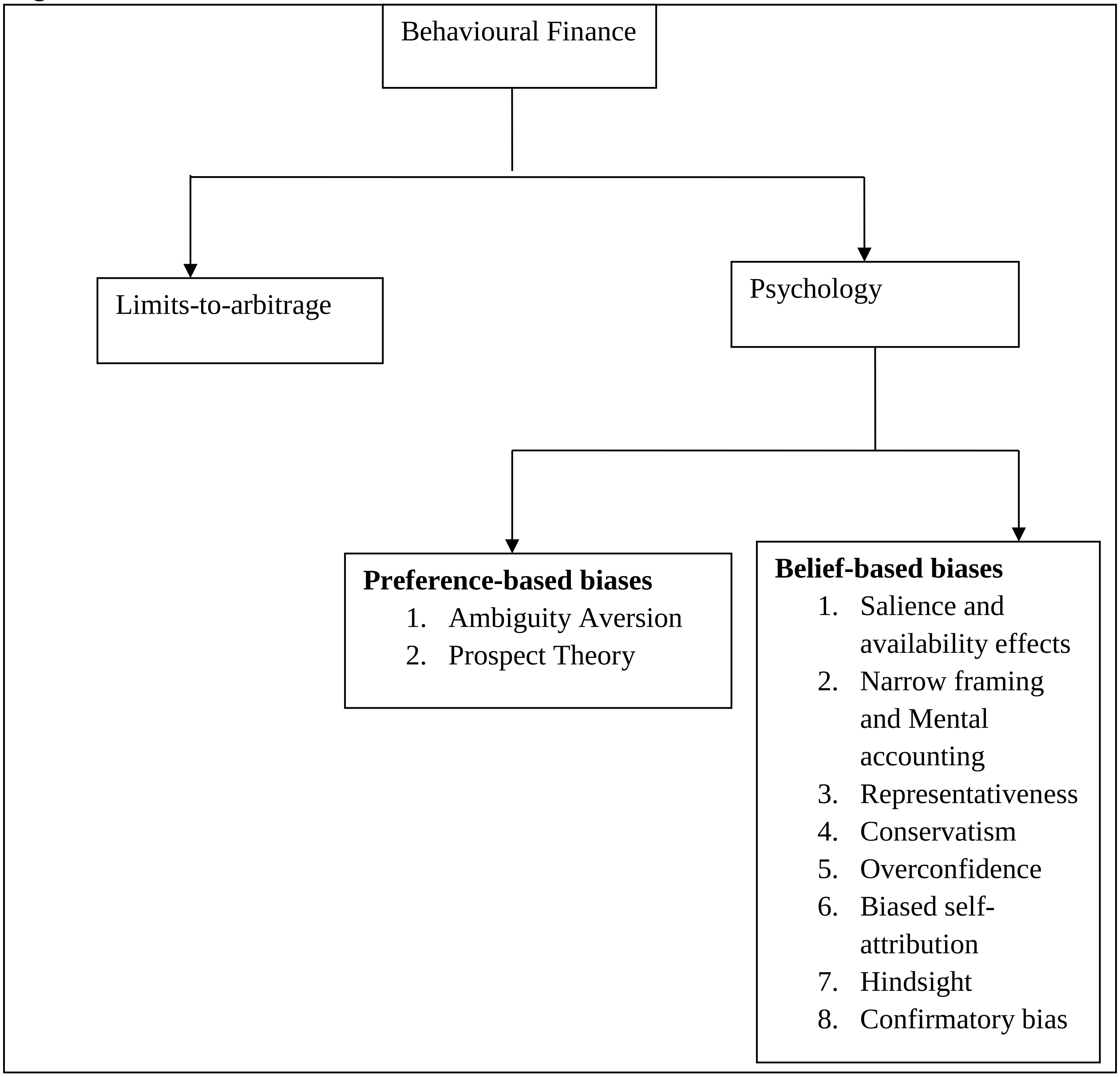
[6] This study only reviews one such outcome which is the index effects.

analysis, behavioural finance attempts to apply concepts from psychology in order to enrich financial analysis.

Just like the traditional finance school has the EMH and the CAPM as its cornerstones (Frankfurter and McGoun, 2002), the behavioural finance school's cornerstones are cognitive psychology (how people think) and the limits-to-arbitrage (when markets are inefficient) (Ritter, 2003; Barberis and Thaler, 2003). We schematise the various components of behavioural finance along its pillars in Figure 2.1. This schematic illustration serves as a guide to the study's entire behavioural finance literature review.

Figure 2.1 shows that behavioural finance has two pillars- limits-to-arbitrage and psychology. The former deals with inefficient markets whereas the later handles preference-based and belief-based biases that are direct products of experiments in psychology. We briefly describe what is entailed in each of the two pillars in subsections 2.2.2.1 and 2.2.2.2.

Figure 2.1: A Schematic illustration of the Behavioural Finance Pillars



Source: Author's own formulation based on Barberis and Thaler (2003).

2.2.2.1 Limits- to- arbitrage theory

Traditional finance's assertion that the law of one price holds and hence market efficiency is premised on the role arbitrage plays in wiping out mispricings in the market. Shleifer and

Vishny (1997) define arbitrage as the simultaneous purchase and sale of the same or essentially similar securities in two different markets for advantageously different prices. From a theoretical point of view, such arbitrage requires no capital and entails no risk although in practice this might not be the case. Arbitrage plays a central role in the analysis of securities markets because its effect is to bring prices to fundamental values and to keep markets efficient given the presence of rational agents.

The rationale behind the limits-to-arbitrage theory is that in the presence of deviations of asset prices from their fundamental values (mispricings), investment strategies employed by arbitrageurs to correct the mispricing can be both risky and costly and as a result, the mispricing can remain unabated. One can employ the agency model of Shleifer and Vishny (1997) in highlighting the intricacies of the limits-to-arbitrage theory.

The main thrust of Shleifer and Vishny (1997)'s agency model of limited arbitrage is the agency problem involved in the practical world of arbitrage. In this model, a market is assumed to contain three sets of players- noise traders, arbitrageurs and investors in arbitrage funds. Individuals investing in arbitrage funds do not conduct trade directly, but instead delegate arbitrageurs who are specialists and rational-decision makers. In return, these arbitrageurs receive payment for their services. Further, the model assumes a particular market where a specific asset is traded during a given (finite) time horizon. In addition, the arbitrageurs only know the fundamental value of the asset sometimes and at certain times its known by both the arbitrageurs and noise traders but the investors never get to know it.

Arbitrageurs who earn high returns in the market are likely to attract more investment resources from the investors who want to share in these returns.

The market for securities is subject to noise trader risk that arises when noise traders' pessimism changes during the trading periods or intervals. In other words, a "pessimism shock" may signify a noise trader misperception of the market fundamentals and thereby lead to a mispricing. The professional arbitrageurs who actually run the trading of assets for the investors are expected to take positions that maximise their clients' expected utility in the presence of any observed mispricing. What this translates into is that arbitrageurs who produce a non-negative return for the investors in one period will be seen as expected utility maximisers and will therefore be entrusted with more resources to invest in the future. Investors have no scientific way of determining which arbitrageur to entrust their resources with other than studying the arbitrageurs' past returns. The investors' allocation of funds to the arbitrageurs in the subsequent period is an increasing function of the arbitrageurs' gross return in the closing period. This is what Shleifer and Vishny (1997) have termed as performance-based arbitrage.

The challenge faced by an arbitrageur who earns negative returns is that some investors might withdraw their funds from him because they think that he is not good enough in the business. However, Shleifer and Vishny (1997) argue that poor performance of the arbitrageur could be indeed attributed to his inferior ability or the worsening of noise trader sentiment or it could be simply a random error. It is difficult a task for investors to ascertain the ability of arbitrageurs in the market. The fact that investors tend to withdraw their resources from arbitrageurs in the face of increased noise trader sentiment for fear of losing resources means that the mispricing might not be fully exploited. The investors' behaviour is a rational approach because their only way of determining the arbitrageurs' abilities is by observing past returns.

Further, other costs and market risks compound decision-making in the market. De Long *et al.*, (1990) and Shleifer and Vishny (1997) describe noise trader risk as one that might arise in the event that the mispricing being exploited by the arbitrageur worsens in the short run. The danger with this kind of risk is that it can force arbitrageurs to liquidate their positions early, resulting in steep losses (Barberis and Thaler, 2003). Much as the arbitrageurs' activities are of interest to the investors, the latter have limited capacity in ascertaining the level of effort the former exerts in exploiting a given mispricing. Accordingly, investors lacking the specialised knowledge to evaluate the arbitrageur's investment strategy would base the evaluation of the arbitrageur on past returns. The worsening of a mispricing in the short-run that the arbitrageur is trying to exploit might lead to negative returns that the investors can interpret as incompetence of the arbitrageur and therefore withdraw their resources. When this happens, it forces the arbitrageur to liquidate his position prematurely a factor that renders him less aggressive in abating the mispricing. Hence, noise trader risk plays a role of forcing the arbitrageur to be more cautious when dealing with the mispricing and as a result the market may witness a long-lasting mispricing.

Additionally, there is fundamental risk that relates to the long run when asset prices fail to converge to the fundamental price of the security due to the arrival of new fundamental information. For example, an arbitrageur who buys a mispriced security whose price is lower than its fundamental value will experience losses in the event of the inflow of negative news about that security. Not even the acts of shorting a substitute security when one buys a mispriced security can an arbitrageur avoid fundamental risk. This is so because it is hard to find securities that are perfect substitutes for one another. Barberis and Thaler (2003) further assert that even if a substitute security exists, it may itself be mispriced.

Apart from the risks involved, arbitrageurs also face several costs. There are information costs of finding and learning about the mispricing as well as the costs required to exploit it. There are transaction costs such as bid-ask spreads, commissions as well as short sale constraints that make the process of exploiting the mispricing hard. It is therefore impossible to wipe out any mispricings that arise in the market.

In brief, the limits-to-arbitrage theory, illustrates why the occurrence of mispricings of asset prices do not necessarily present profit opportunities to arbitrageurs and other rational investors. This is often the case because for one to engage in arbitrage, one is exposed to both costs and risks that might make arbitrage less attractive thereby leading to the persistence of deviations from fundamental value. To complicate matters further is the fact that it is hard a task identifying the presence of a mispricing in the first place and then profiteering from it later. It therefore remains an empirical question whether one can identify a mispricing and subsequently profit from it- this is the task that this study seeks to address.

2.2.2.2 Psychology

Apart from the limited arbitrage argument in explaining systematic mispricing in markets, behavioural finance theorists further argue that investors exhibit information-processing biases. These biases are correlated across individuals so much so that in aggregate their effect is not cancelled out or diversified away (Chan *et al*., 2004).

It is through psychology-the second pillar of behavioural finance- that human information-processing biases can be explained as well as some of the anomalous market phenomena. Psychologists have long established that the scarcity of cognitive resources such as time, memory and attention leads to judgement and decision biases .With a finite human information processing capacity, Simon (1955) and Tversky and Kahneman (1974) observe that individuals use heuristics (imperfect decision making procedures) so as to arrive at reasonably good decisions cheaply. This abbreviation of decision processes is what Daniel *et al*. (2002) and Hirshleifer (2001) term as heuristic simplification. Further, the self-deception theory explains another source of bias in individual decision-making. This argues that individuals are designed to think they are better (smarter, stronger, better friends) than they really are. Lastly, individuals are subject to emotions that can overpower their reasoning thereby causing biased decisions.

We can therefore argue that heuristic simplification, self-deception and emotion-based judgements are the underlying explanations for the known judgment and decision biases. Using Figure 2.1, the literature on psychology follows two channels[7]- that is the preference-based and the belief-based biases whose origins is in heuristic simplification, self-deception and emotion-based judgments.

(a) Preference- based biases

These kinds of biases relate to the way individuals or investors evaluate risky gambles in the financial market (Barberis and Thaler, 2003). Whereas belief-based biases aim at explaining the psychology underlying individual beliefs about given events, preference-based biases are intended to depict the psychology of choice when uncertainty is wide-spread. There are two common examples of preference-based biases, namely, ambiguity aversion and prospect theory.

(i) Ambiguity aversion

This refers to the aversion or dislike of individuals to events where the probability distribution is uncertain. According to Hirshleifer (2001) and Kalayci and Basdas (2010), ambiguity aversion is normally demonstrated by one violation of the expected utility theory that is termed as the Ellsberg paradox. This paradox is popularly demonstrated as individuals' preference for a bet on an urn where it is known that there are 50 red and 50

[7] These concepts are all from the discipline of psychology it is therefore our wish to simply describe them briefly. Nevertheless, the overconfidence theory which is one of this study's objectives is described in details in terms of the psychological and financial content.

blue balls rather than an urn where there are 100 balls with uncertain amounts of each. This kind of choice has also been called as the “preference for the familiar”.

Ambiguity aversion reflects a more general tendency for emotions such as fear to affect risky choices because the individual feels that his competence at choice is being tested. A possible explanation for ambiguity aversion is that the obvious absence of an identifiable parameter of the decision problem may often be associated with higher risk and the possibility of hostile manipulation (Hirshleifer 2001, pp.1550). It is for this reason that individuals prefer gambles that give them a sense of understanding or competence in whatever they set out to do.

(ii) Prospect theory

In a pioneering article, Kahneman and Tversky (1979) developed the prospect theory that is considered as a psychologically realistic alternative to the Von Neumann Morgenstern expected utility theory. It serves as a descriptive theory of choice under uncertainty. Specifically, it describes individual choice behaviour in the presence of alternative risky gambles (Shefrin and Statman, 1985; Kalayci and Basdas, 2010). Prospect theory departs from the expected utility framework in which agents are assumed to be utility maximisers whose preferences satisfy the axioms of completeness, transitivity, continuity and independence. Psychological experiments show that individuals violate expected utility principles when choosing among risky gambles (Hirshleifer, 2001; Barberis and Thaler, 2003). In addition, another major difference between prospect theory and expected utility is that the former is a descriptive theory that focuses on changes in wealth whereas the latter is a normative theory that uses levels of wealth.

Thaler and Barberis (2003, pp.1067), emphasise that the success of prospect theory over all other non-expected utility theories[8] is due to its explanatory power of experimental results. The problem with the non-expected utility theories is that they try to capture some of the anomalous experimental evidence by slightly weakening expected utility axioms. The difficulty with such models is that in trying to achieve two goals- normative and descriptive- they end up doing an unsatisfactory job altogether. In contrast, prospect theory has no aspirations as a normative theory: it simply tries to capture individuals' attitudes to risky gambles as parsimoniously as possible.

(b) Belief-based biases

These are individual biases that explain the psychology underlying beliefs about given events. This is important to economists studying financial markets because it informs us how agents form expectations. The belief-based biases that we tackle here include salience and availability effects; narrow framing and mental accounting; representativeness; belief updating and conservatism; all these are an outcome of heuristic simplification. We also tackle overconfidence, biased-self attribution, hindsight bias and confirmatory bias as outcomes of the self-deception theory. Nevertheless, we need to point out that all biases are somewhat emotion-driven.

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[8] Other non-expected utility theories include- weighted-utility theory, implicit expected utility, disappointment aversion, regret theory and rank-dependent utility theories.

(i) Salience and availability effects

According to Barberis and Thaler (2003), when individuals are asked to judge the probability of occurrence of a given event, they often search their memories for relevant information. Limited attention, memory and processing capacities force individuals to focus on subsets of available information as opposed to all the information. Accordingly, Tversky and Kahneman (1974) assert that an information signal is salient if it has characteristics from the past state that are good at hooking our attention or at creating associations that facilitate recall. In addition, items that are easier to recall are seen to be more common. Hirshleifer (2001) argues that it makes sense or it is rational for people to easily recall things that are more common (reported more often).

(ii) Narrow framing and mental accounting

Narrow framing involves compartmentalising problems and then analysing them in too isolated a fashion because of limited time and cognitive resources (Hirshleifer, 2001). The concept of mental accounting compliments that of narrow framing. Whereas Thaler (1985) views mental accounting as a kind of narrow framing in which individuals try to keep track of their gains and losses decisions into separate mental accounts, Thaler (1999) views it as the set of cognitive operations used by individuals and households to organise, evaluate and keep track of financial activities. In other words, individuals have a tendency of subconsciously separating related decision problems into separate mental accounts as they try to evaluate different outcomes (Ritter, 2003). This kind of separation becomes a source of judgement and decision biases in financial markets; for example the disposition effect of Shefrin and Statman (1985) is explained by mental accounting biases.

(iii) Representativeness

The representativeness heuristic involves assessing the probability of a state of the world based on the degree to which the evidence is perceived similar to the state of the world. It therefore translates into the tendency for individuals to classify things into discrete groups or categories based on similar characteristics (Hirshleifer, 2001). Similarity is viewed as an indicator of the conditional probability of the evidence given the state of the world versus other states. However, a Bayesian also takes into account heavily the prior probability of the outcomes whereas people tend to underweight statements about unconditional population frequencies in performing conditional updating- base rate underweighting.[9]

Ritter (2003) provides an example of how the representativeness heuristic applies to financial markets: investors interpreting the occurrence of high equity returns over time as a 'normal' event. Chan *et al*. (2004) further assert that because investors are bent towards classifying events by looking at their similarities, they forget that extreme observations are unlikely to be repeated. This means that after a series of past high performance of equities, investors are disappointed when future performances revert to the mean. Therefore the representativeness heuristic would imply that following consistent past performance of a

[9] Chan *et al*. (2004) offer the following simple example to add meaning to base rate underweighting or neglect- people may think that a rock is gold because of its salient features like colour and weight and in doing so they fail to consider the low probability of finding gold (which is actually the base rate).

given security, investors are forced to give it a category and implicitly form biased expectations about its future performance.

(iv) Conservatism

The idea of conservatism relates to the process through which agents are known to update their beliefs following arrival of new evidence. Hirshleifer (2001) and Chan *et al*. (2004) define conservatism bias as individuals' tendencies to update their beliefs too slowly relative to Bayes' rule. That is, individuals over-use the base rate and under-use the information in the evidence, which means they overweight their prior beliefs and underweight the sample evidence. Conservative individuals might not revise sufficiently (using Bayes' rule) their beliefs about future earnings upon observing a good earnings outcome or a series of good earnings outcomes; this is the exact opposite of the representative heuristic.

Hirshleifer (2001) offers the costly information processing argument as a possible explanation for the conservatism bias, that is to say, processing new information and updating beliefs is costly. Experimental psychological evidence indicates that information presented in a cognitively costly form is weighed less whereas information that is abstract and statistical, such as sample size and probabilistic base-rate information is overweighed. Further, base rate underweighting is also explained by the costly information processing argument in the sense that if an individual under weighs new information received about population frequencies (base rates), then base rate underweighting is a form of conservatism. The costly-processing-of-new information argument does not suggest that an individual will underweight his pre-existing internalised prior beliefs. The interpretation of base rate underweighting and conservatism due to Griffin and Tverskey (1992) alludes to under reaction versus overreaction to signals, which translates into the effect of excessive reliance on the strength of information signals and under reliance on the weight of information signals.

(v) Hindsight bias

Hindsight bias is described in psychology literature as a tendency to think you 'knew it all along' in an effort for a decision maker to maintain their self esteem after an earlier decision (Hirshleifer, 2001 and Daniel *et al*., 2002). In this bias, individuals are ready to devise and apparently believe their explanations for alleged facts about the world and themselves. The hindsight bias is related to another bias that has been termed as rationalisation- straining to come up with arguments in favour of one's past judgements and choices.

(vi) Confirmatory bias

This kind of bias involves the practice of interpreting ambiguous evidence in a fashion that is consistent with prior beliefs of the individuals. Individuals give careful scrutiny to inconsistent facts and explain them as due to luck or faulty data gathering (Hirshleifer, 2001). In an experimental market setting, individuals who are more subject to confirmatory bias lose money to those who are less subject to it. Confirmatory bias may cause some investors to stick to unsuccessful trading strategies and this may cause persistent mispricing.

(vii) Overconfidence

The self-deception theory implies occurrence of overconfidence among agents or individuals in a number of ways (Hirshleifer, 2001). The literature on the calibration of subjective probabilities depicts individuals both professionals and non-professional as overestimating the precision of their knowledge (Odean, 1998b). Additionally, the best-established finding in the calibration literature is that individuals tend to be overconfident in answering questions of moderate to extreme difficulty. Exceptions to overconfidence in calibration are that individuals tend to be under confident when answering easy questions and they tend to be well calibrated when predictability is high and when performing repetitive tasks with fast, clear feedback.

Furthermore, individuals are unrealistically optimistic about future events, with a great expectation that good things will happen to them more often than to their peers. More interesting is the discovery that individuals seem to be unrealistically optimistic about even chance games. For example a study of Japanese foreign exchange dealers shows that participants are more optimistic that the exchange rate movements will affect them positively as compared with other market competitors (Ito, 1990).

Greenwald (1980) shows that psychological evidence suggests that most individuals have unrealistically positive self-evaluations; they rank themselves as better than the average individual and see themselves better than others see them. Additionally, individuals rate their abilities and prospects higher than those of their peers. Most individuals also overestimate their own contributions to past positive outcomes, recalling information related to their successes more easily than that related to their failures. Moreover, when they anticipate a certain outcome and the outcome then occurs, individuals often overestimate the degree to which they were instrumental in bringing it about.

The outcome of biased beliefs in one's abilities and excessive optimism brings about higher motivation, greater persistence, performance that is more effective and ultimately greater success (Taylor and Brown, 1988). However, as far as our study is concerned, exaggerated beliefs and excessive optimism is likely to lead to biased judgements most especially among investors and security analysts (Odean, 1998b). Judgement and decision-making entails making inference from available information sets by various agents who have inherent prior beliefs.

While making inference given a set of information, individuals over weight salient information (information that stands out and captures attention), give too much consideration to how extreme information is and not enough to its validity. Individuals often behave as though information is to be trusted regardless of its source, and make equally confident inference regardless of the information's predictive value (Odean, 1998b). They overweight information that is consistent with their existing beliefs, are prone to gather information that supports these beliefs and readily dismiss information that does not. Generally, given psychological experiences, one would expect individuals to overreact to less relevant, more attention grabbing information while under reacting to important abstract information. In particular, one might expect individuals to underestimate the importance of single statistics that summarise a large sample of relevant data, for example corporate earnings.

In financial markets, analysts and investors generate information for trading through different means, such as interviewing management, verifying rumours and analysing financial statements that can be executed with varying degrees of skill. Daniel *et al*. (1998) observe that if an investor overestimates their ability to generate information or to identify the significance of existing data that others neglect, then they will underestimate their forecast errors. If they are more overconfident about signals or assessments with which they have greater personal involvement, they will tend to be more overconfident about the information they have generated but not about public signals. Hence, an overconfident investor is one who overestimates the precision of their private information signal, but not of information signals publicly received by all.

(viii) Biased self-attribution

One would expect individuals to have learnt from their earlier mistakes or biases when they make subsequent judgements and decisions. In other words, the rational learning process over time would eliminate the overconfidence bias, which has its theoretical foundation in the self-deception theory. Overconfidence and biased self-attribution are static and dynamic counterparts; self-attribution causes individuals to learn to be overconfident rather than converging to an accurate self-assessment (Hirshleifer, 2001). In order for the self-deception theory to be able to explain the persistence of the judgemental biases, nature must provide mechanisms that bias the learning process. This is achieved through the process of self-enhancing biased self-attribution that is nothing but a variation in confidence than further biases in judgement (Daniel *et al*., 1998).

Taylor and Brown (1988) define biased self-attribution as the tendency of individuals to attribute good outcomes to their own abilities and bad outcomes to external circumstances. This further means that as individuals observe the outcome of their actions, they update their confidence in their own ability in a biased manner (Odean, 1998b). Biased self-attribution is actually an outgrowth of the attribution theory in the discipline of psychology. It asserts that individuals too strongly attribute events that confirm the validity of their actions to high ability and events that disconfirm their action to external noise or sabotage. Accordingly, this self-attribution bias assertion also relates to the notion of cognitive dissonance in which individuals internally suppress information that conflicts with past choices.

2.2.3 Testable theories in Behavioural Finance

2.2.3.1 Limits- to- arbitrage - index revision theories

Barberis and Thaler (2003) pose a fundamental question that this study uses in order to achieve one of the study’s objectives of testing for the impact of stock inclusions into and exclusions from the market index on the affected stocks. The question they formulate is that “whereas from a theoretical point of view there is reason to believe that arbitrage is limited and therefore it is only of limited effectiveness, is there any evidence that arbitrage is limited?’’

The answer to the above question is an empirical one and Barberis and Thaler (2003) offer a useful insight to the empirical approach that this study adopts in depicting the limits of arbitrage. They argue that in principle, any example of persistent mispricing is immediate evidence of limited arbitrage: if arbitrage were not limited, the mispricing would quickly disappear. One example of persistent mispricing illustrated in the literature is that of stock inclusions into and exclusions from the market index or changes in the composition of the stock market index.

Bildik and Gulay (2008) observe that changes in the index composition provide a unique opportunity to examine the price behaviour in stock markets. Specifically, the occurrence of the price pressure when a stock is added to or deleted from a widely followed index; a phenomenon that is described by Kappou *et al*. (2010) as the 'index effect' is given a number of theoretical justifications. Following enormous evidence from a number of studies, one can observe that stocks included in (excluded from) a widely followed index exhibit significant positive (negative) abnormal returns on the announcement day and that trading volume is also affected by the event. This result is inconsistent with the EMH, which assumes that security prices reflect all available information. Consequently, a number of theories explain this index effect behaviour and these are discussed here below.

(i) The Price Pressure Hypothesis (PPH)

The main prediction of the PPH is that there will be a temporary increase (decrease) in the price of a newly added (deleted) stock of a given index as well as increased trading volume. To appreciate the PPH and even the Imperfect Substitution Hypothesis (ISH) that we will discuss later, one needs to revisit Scholes (1972) and Kraus and Stoll (1972) who explain why a large stock sale (purchase) causes the price to decrease (increase) even when no new information is associated with the transaction.

Scholes (1972) is seen as the founder of the PPH although his original analysis is applied to secondary offerings. He starts by asserting that few people would disagree with the idea that buyers and sellers of shares on an organised exchange can buy and sell small quantities of stock at approximately the prevailing market price. Nevertheless, when the size of the stock is large relative to these small trades, there is a belief that the price of the stock must fall to induce investors to purchase these additional shares. This inducement or "sweetener" as Scholes (1972) calls it results from an increase in the quantity of shares that must be held by market participants. If the excess demand curve for shares is downward sloping, the additional shares will only be held at lower prices and the direct consequence of buying shares at lower prices to purchasers is a subsequent extra profit or "sweetener".

Put differently, when a large block of stocks is introduced or sold in the market, one should expect to see a down-ward price adjustment in the price of the stock. This fall is the expected value of information contained in large-block trades. In the framework of Scholes (1972), price –pressure adherents view the price adjustments as being caused by the down-ward sloping nature of the demand curve for shares and not to a change in the equilibrium value of the firm.

The Scholes (1972) classic study is about secondary offerings and not index inclusions or exclusions. However, it lays a background to both the PPH and ISH that are used in explaining index effects because adding a new stock in a market index is implicitly equated to a secondary offering and perhaps most importantly is that both events are assumed to be information-free. The question that arises then is that, if index revisions are information-free events why are they followed by price pressures. According to Scholes (1972), the answer lies in the shape of the demand curve of stocks. Hence, the resulting price pressure observed following large transactions might affect security prices even in the absence of new information due to demand curves that are less than perfectly elastic.

The PPH when applied to index revisions explains why the price of a stock that is added to (deleted from) the index increases (decreases) following the announcement of the revision. Harris and Gurel (1986) assert that the PPH assumes that prices increase before the change date by the excess demand of fund managers and then reverse after the change date since passive sellers are attracted by the price increases that push the prices above their equilibrium levels. In other words the PPH suggests that if stocks have short-term downward sloping demand curves, their prices should be momentarily affected due to index funds executing substantial purchases (sells) of the added (deleted) stocks, but that effect should disappear once the excess demand is satisfied (Mazouz and Saadouni, 2007; Bildik and Gulay, 2008).

In many developed and emerging markets, there exist large index funds. In practice, many large index funds mimic the performance of a benchmark index that is widely followed by holding a portfolio of the stocks included in the index and employing the same weights used to compute the index. When the benchmark's index composition changes, the index fund managers frequently purchase the added stocks and sell the deleted stocks within a few days around the change date. The potential shift in demand can be quite large based upon the total money invested in index funds and other institutional investors who use the index as a benchmark. However, most importantly, Bildik and Gulay (2008) assert that although changes in index composition convey no new information, they do shift demand.

In markets where index funds are insignificant, most especially in pre-emerging markets in Africa, the price pressures that follow additions and deletions could be attributed to the trading strategies employed by large institutional investors who employ investment strategies that seek to match the index return by purchasing the stocks newly added to the index (Pruitt and Wei, 1989). Besides this, there are other explanations offered in different theories to give meaning to the observed price pressure that follows additions and deletions.

In summary the main prediction of the PPH is that, there will be a temporary increase (decrease) in the price of a newly added (deleted) stock from the index whereas trading volume may increase temporarily in both cases.

(ii) The Imperfect Substitutes Hypothesis

The imperfect substitution hypothesis (ISH) or downward-sloping demand curve for stocks hypothesis (DSDC) also has its roots in Scholes (1972)'s examination of security markets that focuses on substitution versus the price pressure theories. He considers securities in capital markets as not being closely related and the uniqueness or characteristics particular to an individual asset makes each asset stand apart from other assets in the market. Hence, in the event that a particular firm decides to increase its shares outstanding, the additional shares will have to be sold at a discount from existing market prices in order to attract new buyers to the new issue. The magnitude of the discount is an increasing function of the size of the issue.

A firm that issues additional outstanding shares simply adds to the stock of assets that must be held. At the time of the new issue, there should be no effect on the market price of the firm's existing shares because the new issue is simply an augmentation of the existing shares. In the event that there is an observed change in the market price of the firm's shares, it cannot be attributed to the new issue but instead it is due to adjustments that equate prices of similar income streams of market assets, which are close substitutes.

The market's pricing of securities of similar risk allows for a uniform expected rate of return across all such securities. If any particular asset should be selling to yield a higher expected return due solely to the increase in the quantity of shares outstanding, this would indicate that investors expect to realise abnormal returns on this asset. However, investors noticing these profit opportunities would soon arbitrage them away.

According to Scholes (1972), the substitution hypothesis implies that there cannot be profit opportunities that result from the increase in the quantity of shares that must be held. Since assets are substitutes in investor portfolios, the pure price effects of corporate new issues or investor purchases and sales must be very small. The substitution hypothesis would therefore imply that the inducement necessary to sell large quantities of stock would be close to zero. When applied to the theory of index revisions, the ISH/DSDC still predicts that the stock that is added to (deleted from) a given index will have its price increase (decrease) after the announcement where as the trading volumes increase significantly and remain at high levels after the change date for the added stock.

The ISH in index revisions literature is first formalised by Shleifer (1986) who asserts that when stocks are added to the index they cease to be substitutes for each other. Consequently, the main result in this theory then is that if stocks added to the index have no perfect substitutes, a rightward shift in demand for these stocks (driven by index funds) result in higher prices (Kaul *et al*., 2000; Bildik and Gulay, 2008). It is this assumption that securities are not close substitutes for each other that leads to the long-run demand curve for securities which is less than perfectly elastic. The equilibrium prices therefore change when demand curves shift to eliminate excess demand. One does not expect price reversals because the new price reflects a new equilibrium distribution of security holders.

In summary, the ISH predicts a permanent price effect from index revisions. Index investors purchase stocks that enter the index and sell those that are removed. Because other stocks are imperfect substitutes, arbitrageurs cannot provide the market with liquidity as in the PPH. The reduced supply of a stock results in a higher equilibrium price and vice versa.

(iii) Information Content Hypothesis (ICH)/Information Hypothesis

Woolridge and Ghosh (1986) argue that in an efficient capital market, the inclusion or exclusion of a firm in a broad index of market valuation has no effect on the value of its common shares if the inclusion or exclusion conveys no information to investors. The criteria used in index revisions are public information in a number of market settings. For example in the revision of the S&P 500, Standard and Poor's Corporation states categorically that the investment appeal of the stocks does not enter into the selection process that is used when firms are added or dropped from the S &P 500. Jain (1987) argues that even though the decision to include or exclude a stock may not imply any judgement about its investment appeal on the part of Standard and Poor's, the announcement of inclusion or exclusion may impart information to the investing public that changes their perception of the stock's investment appeal.

The ICH theorists contend that an index revision comprises information about a company's future performance. As a result, inclusion results in a permanent increase in price while exclusion is bad fundamental news that brings a one-time price drop (Doeswijk, 2005). The

ICH theorists emphasise that index revisions are events that actually convey meaningful information such as improved or expected operating performance to investors about the affected stocks leading to permanent price and volume changes (Jain, 1987; Dhillon and Johnson, 1991; Yun and Kim, 2010; Liu, 2011). The information hypothesis implicitly suggests that much as stock market index revisions are guided by known criteria, they actually use non-public information in selecting stocks for additions to the index; this is what partially explains the public's perception of an addition to mean good news and an exclusion to mean bad news (Hegde and McDermott, 2003).

Briefly, the main predictions of the ICH are that an addition of a stock to the index causes its price to rise permanently and its volume to increase temporarily whereas a deletion leads to a permanent price decline and a temporary increase in the volume.

(iv) Liquidity Cost Hypothesis (LCH)

The LCH is attributed to Amihud and Mendelson (1986) who argue that liquidity, marketability or trading costs are among the primary attributes of many investment plans and financial instruments. In the securities industry, portfolio managers and investment consultants tailor portfolios to fit their clients' investment horizons and liquidity objectives. It is against this background that the LCH theorists argue that institutional and other larger investors may realise some benefits in trading relatively liquid stocks as opposed to relatively illiquid stocks because of the potential pricing effects of trading in large blocks (Woolridge and Ghosh, 1986).

Consequently, if liquidity increases (decreases) permanently as a result of a firm being added to (deleted from) an index like the S&P 500, its share prices may rise (fall) to reflect the perceived value of liquidity to institutions and other large investors. More still, the LCH posits that a decrease (increase) in liquidity would cause a permanent increase (decrease) in security prices.

The LCH postulates that index revisions affect the liquidity of a stock in that an inclusion into the index results in increased liquidity with lower trading costs and higher trading volumes with a one-time jump in its share price. For index exclusions, there is a reduced liquidity of the affected stock with higher trading costs and lower trading volumes as well as a reduction in the share price (Doeswijk, 2005). The resultant price effect is permanent in both cases.

Hegde and McDermott (2003) argue that the addition of a stock to an index specifically the S&P500, is associated with many significant changes in its ownership and trading activity that affect its market liquidity. By far, the most important of these changes is a shift in ownership composition to uninformed index investors. Other potential significant changes that can affect liquidity include a change in the character of order flow, increased analyst following, increased arbitrage trading activity and order flow migration of liquidity traders from the stock market to the market for index products. Hegde and McDermott (2003) further note that much as these explanations for the liquidity hypothesis seem different, they are observationally equivalent.

Briefly, one expects to observe an increase (decrease) in liquidity for stocks added to (deleted from) the index. Hence the main prediction of the LCH is that following stock additions to (deletions from) the index, there is an observed permanent price and volume (increase) decrease. Inclusion into the index is beneficial for the stock since trading is more frequent and leads to reduced costs of trading, while the exclusion causes the reverse that is reduced trading and high trading costs.

(v) Attention Hypothesis/Investor Awareness Hypothesis (IAH)

The attention hypothesis or investor awareness hypothesis (IAH) is pioneered by Merton (1987). This theory argues that an increase in the relative size of a firm's investor base reduces its cost of capital and increases its market value. A firm's investor base can increase at zero cost if for example a newspaper or other mass media coverage about it reaches a large number of investors who are not currently its shareholders. This media coverage could induce some of this large number of potential investors to incur the set-up costs and follow or invest in the firm. Even if the news regarding the firm might not be new to existing shareholders, if its release however is followed by the influx of new shareholders, then this is perceived as expanding the firm's investor base, which will also be followed by a rise in the stock price. As such, Merton (1987) argues that stock prices sometimes react to a broad and widely circulated report about the firm even when all the substantive information in the report has been previously announced.

In this model, marginal changes in press coverage draw investors' attention to the firm resulting in an increase in the value of a firm. Polonchek and Krehbiel (1994) assert that while professional investors may be cognisant of information that affects the value of firms, investors who do not continuously monitor firms are the ones who will be attracted to a firm at the margin because of broad media coverage associated with an index change. Firms dropped from an index should not experience a significant price change. Removal from an index will not affect the number of investors who have already incurred the information costs associated with including a firm in their optimal portfolio. The value of a firm dropped is not expected to decline since the announcements do not contain any firm-specific information.

The IAH implies that if one stock enters into the index, investor awareness of the stock will be higher than before and many investors will seriously consider buying it. With increased investors' awareness regarding an added stock comes a reduction in the shadow cost[10] of incomplete information, which results in higher stock prices. However, if a given stock drops out of the index, the awareness of that stock will not diminish and the shadow cost will not increase quickly. The premise that index revisions appear in the media is central in the awareness hypothesis (Doeswijk, 2005).

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[10] Merton (1987) shows that there are two categories of investors: the informed and the uninformed who all feel comfortable trading in the securities they are aware of (for example, NSE 20 constituent stocks). In a segmented market, investors hold portfolios that are incompletely diversified. The difference in the required rate of return between a completely diversified portfolio and an incompletely diversified one is Merton's shadow cost.

Briefly, the main predictions of the IAH are that index additions deliver a positive permanent price effect because they are new to a certain group of investors while deletions being stocks that are already well known are unaffected since the news neither changes the investor base nor contains fundamental information. No conclusive predictions are made over trading volume behaviour in this theory. Volume effects, if present, are expected to be short-lived and only associated with announcements of additions.

2.2.3.2 Psychology-Overconfidence theory

(i) Modelling Overconfidence in finance literature

It has already been pointed out that overconfidence is both static and dynamic in nature. Consequently, finance theorists use static and dynamic models to capture overconfidence (in the static sense) and its counter-part of biased self-attribution (in the dynamic sense). The theoretical modelling presented here is due to Daniel *et al*. (1998) who describe overconfidence in both a static and dynamic manner.

(a) The Basic theoretical model: Constant Confidence

There are three basic assumptions in Daniel *et al*. (1998) theoretical model of overconfidence (static confidence). First, each member of a continuous mass of agents is overconfident in the sense that he receives a signal whose precision he overestimates. Traders that receive the signal are referred to as the informed, INF where as those that do not receive it are referred to as the uniformed, UIF. Second, the informed traders are risk neutral whereas the uninformed are risk averse. Third, each individual has an endowment of a basket containing security shares and a risk-free *numeraire* that is a claim to one unit of terminal-period wealth.

The analysis follows four key dates or periods in which the differences in the arrival and interpretation of information signals is crucial to the understanding of the dynamics of the model. At period 0, individuals possess identical prior beliefs and trade solely for optimal risk-transfer purposes. At period 1, the informed individuals, *INF* , receive a common noisy private signal about underlying security value and trade with the uninformed individuals, *UIF* . At period 2, a noisy public signal arrives as trade continues to take place. Finally, at period 3, conclusive public information arrives, the security pays a liquidating dividend and consumption takes place[11]. All the random variables involved in the analysis are assumed independent and normally distributed.

The private information signal received by the informed individuals, *INF* during period 1 is captured through the expression in equation 2.1.

(2.1) $S_1 = \pi + \varepsilon \qquad where\, \varepsilon \sim N(0, \sigma_\varepsilon^2)$

In equation (2.1), the private information signal received by the informed individuals, *INF* is denoted S_1 and it is composed of the value of the asset π plus an error or noise estimate ε. During the trading process in period 1, when the informed traders possess their private information signal, the uninformed individuals *UIF* correctly assess the error variance but

[11] The risky security generates a terminal value of π which is assumed to be normally distributed with mean 0 and variance σ_π^2.

the INF individuals underestimate it to be $\sigma_c^2 < \sigma_\varepsilon^2$. The differing beliefs about the noise variance are common knowledge to all groups of traders.

There is release of public information in period 2 and this signal is expressed in equation 2.2 as,

(2.2) $S_2 = \theta + \eta, \qquad where\ \eta \sim N(0, \sigma_p^2)$.

In equation 2.2, the variance (σ_p^2) of the noise term η is correctly estimated by all investors. For the model's predictions to hold it is important that some noisy public information arrives after a private signal. It is because of this requirement that equation 2.2 is in existence. The overconfidence bias (the bias in the private information signal) that is inherent in the buying and selling decisions of the informed investors in this model, operates in a way that it pushes the security prices away from their rational values. This is the case because in attaching so much value to their private signals, the informed risk-neutral individuals end up driving prices from their fully rational values out of equilibrium by the amount of noise in their private signals. Daniel *et al*. (1998) assume that the informed traders' behaviour exhibits risk-neutrality and it is for this reason that the prices of securities in each period satisfy the conditions in equations 2.3, 2.4 and 2.5.

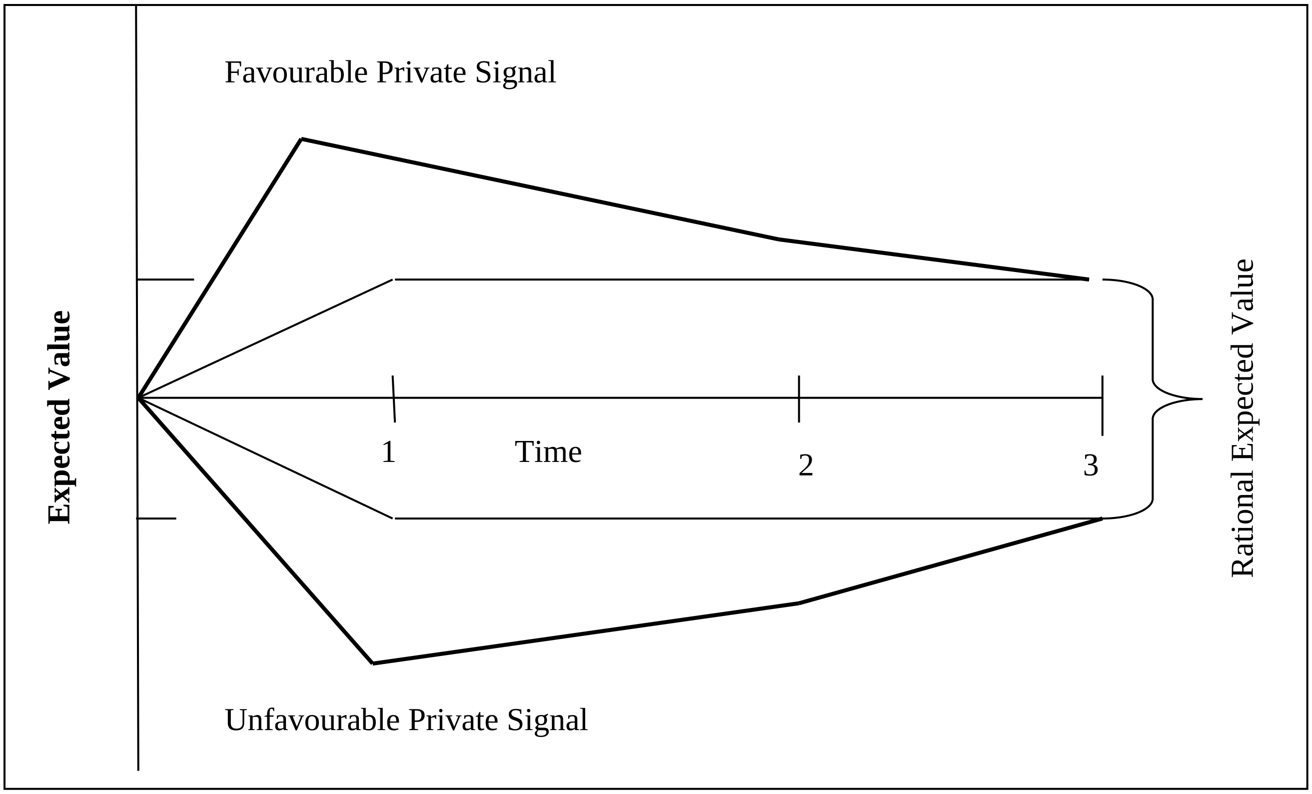
(2.3) $P_1 = E_c[\pi \mid \pi + \varepsilon]$,

(2.4) $P_2 = E_c[\pi \mid \pi + \varepsilon, \pi + \eta]$,

(2.5) $P_3 = \pi$,

where the subscript C denotes the fact that the expectation operator is calculated based on the informed traders' confident beliefs. Equation 2.3 indicates that the security's price is biased by the informed traders' beliefs in their private information signal where as equation 2.4 shows that even when some public information signal is released to all individuals, the informed ones bias prices by over weighting their private information signals. Equation 2.5 indicates that in the absence of all the biases in the information signals, the terminal value of the security will equal to the rational price. We can graphically illustrate the price behaviour and the overconfident traders' behaviour in Figure 2.2.

Figure 2.2: Average market prices as a function of time with overconfident investors.



Source: Daniel *et al*., (1998).

Figure 2.2 depicts the average price path following a positive (upper most curve) or negative (lower most curve) period 1 private signal. The actual curve is an impulse-response function that depicts the expected prices conditional on a private signal of a unit magnitude arriving at time 1. The rational expected values depict the rational prices in the absence of any noise signals. However, with the presence of overconfident traders, the price path differs from the rational one since some individuals interpret their private information signals differently which ultimately results in biases in the prevailing security prices.

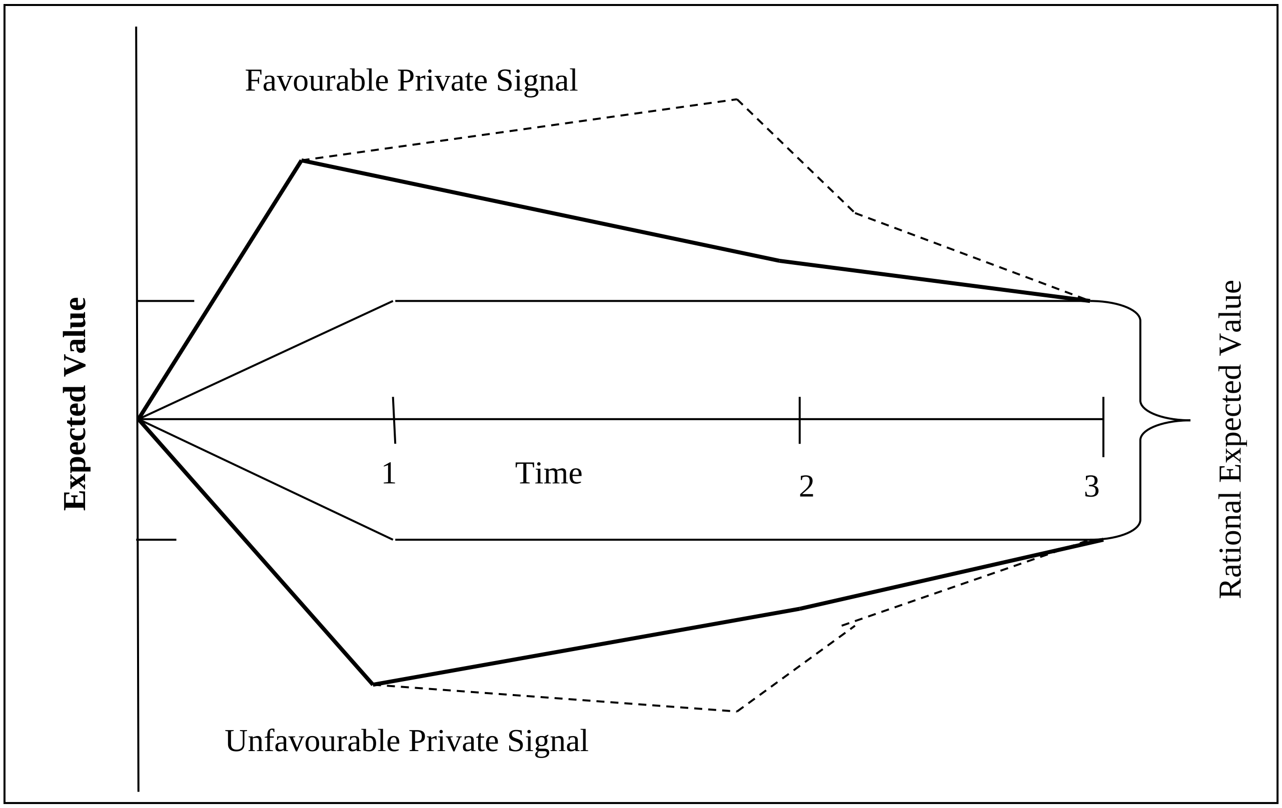
In the presence of a private signal $S_1 = \pi + \varepsilon$, the overconfidence bias inherent among the informed traders causes the period 1 stock prices to overreact to any new information. The resulting price is different from the rational price as depicted by the outermost lines of the graph. Trading in the next season (period 2), bases on the assumption that there is the arrival of a noisy public signal, which has the effect of bringing about the partial correction of the inefficient deviation that occurred in period 1. The correction process continues in subsequent periods especially when more public information which is not noisy arrives. The part of the impulse response prior to the peak is called the overreaction phase while that after the peak is the correction phase.

Daniel *et al*. (1998) argue that the overreaction and correction phases imply covariance between price changes during the various periods. In addition, the security prices' overreaction to the private signal is partially corrected by the arrival of a public signal in period 2 and fully corrected upon release of the period 3 public signal.

(b) Augmenting the constant confidence model: biased self-attribution

Biased-self attribution is the dynamic counterpart of the overconfidence theory. It is premised on the idea that actions and resulting outcomes affect confidence, particularly, events that confirm an individual's beliefs and actions boost confidence too much whilst disconfirming events weaken confidence too little (Daniel *et al*., 1998). This psychological bias translates into short-run momentum in stock prices as well as return predictability. We use a graphical exposition to depict the biased self-attribution in Figure 2.3 by modifying the graph in Figure 2.2.

Figure 2.3: Average market prices as a function of time with overconfident investors: biased self-attribution case



Source: Daniel *et al*., (1998).

From Figure 2.3, an individual or investor's level of confidence accelerates with confirmatory public information that comes after they have made their selling and buying decisions. A confirmatory public information signal is the one that carries the same sign with the individual's private signal. Daniel *et al*. (1998) formulation works on the assumption that if there is a public information signal that confirms the individual's trade, he becomes more confident and if it disconfirms, his confidence decreases slightly or stays constant.

The dashed lines in Figure 2.3 represent the impulse response function for a private signal. The figure shows two possible period 1 prices and the paths for expected price conditional on the period 1 move. The importance of the dashed lines in the figure is to show the outcome-dependent confidence as individuals make choices.

Biased-self attribution is captured by the dashed lines, which prolong the static overconfidence line. What this means is that the individuals who used their private signals to determine the price of the stock during period 1 were able to confirm their signal with the public information signal released during period 1. The fact that their private signal is consistent with the public signal in period 1, the investors continue anticipating the same scenario in the next period (period 2). This explains why investors continue expecting a higher price (returns) in period 2 since the level of confidence will have increased. In period 2 when they realise the variation between their private information signal and the confirmatory public information signal, the investors' level of confidence declines gradually until the stock prices reach their rational price level. It is in the overreaction phase and not in the correction phase that we observe short-term momentum in security prices due to biased-self attribution (Daniel *et al*., 1998).

It can be noted that theoretical finance models the overconfidence bias in a static and dynamic fashion. Static models or models with constant overconfidence overtime assume that there are stable individual differences in the degree of overconfidence where as dynamic models incorporate the changes in overconfidence over time as individuals' investment plans succeed. This partly explains the view that biased self-attribution reinforces overconfidence.

Overall, the proposition that investors are overconfident about their valuation and trading skills translates into intertemporal changes in trading volume. Biased-self attribution causes the level of investor overconfidence and trading volume to vary with past returns. In effect, the intertemporal changes in trading volume are the primary testable implications of the overconfidence theory (Odean, 1998b; Gervais and Odean, 2001). Daniel *et al*. (1998)'s depiction of the overconfidence theory in both its static and dynamic form guides is the theoretical foundation of the empirical models used in this work.

(ii) Basic predictions of overconfidence models

The commonest prediction among almost all overconfidence models is the occurrences of high trading volume in a market infested with overconfident investors (Odean, 1998b; Wang, 1998; Benos, 1998; Gervais and Odean, 2001; Statman *et al*., 2006; Chuang and Lee, 2006).They all contend that overconfidence increases trading volume in stock markets. Odean (1998b) offers an illustration of a market that has three types of overconfident players whose activities affect trading volume: these are price takers, insiders and market makers. The analysis shows that overconfident price takers form differing posterior beliefs and trade speculatively with each other. Were these traders rational, they would hold identical posteriors and trade only to initially balance their portfolios. For overconfident insiders, they also trade aggressively than if they were rational whereas overconfident market makers set a flatter supply curve that encourages more trading when investors are price sensitive. Thus in all the three settings, the overconfidence bias inherent in individuals leads to greater trading volume.[12] Overconfidence models therefore predict that the higher the degree of overconfidence of an investor, the higher is his propensity to trade and this ultimately increases the volume of trade.

Another prediction of overconfidence models is that investors' overconfidence increases volatility in the market. Overconfidence increases volatility by distorting the prices implied by public or broadly disseminated information since different investors interpret them differently. In addition, overconfidence increases volatility by moving prices closer to the values implied by highly concentrated private information. The influence of a group of investors on price will depend on their numbers, wealth, risk tolerance, overconfidence and information (Odean, 1998b). In a market with many investors and few market makers, it is unlikely that dampening of volatility by overconfident market makers will offset increases in volatility due to overconfident investors. By overweighting the aggregate signal of the price-taking investors, overconfidence drives price further from its true underlying value and further from its unconditional mean; this results into increased volatility.

The theories of overconfidence further predict that it (the overconfidence bias) lowers expected utilities since overconfident traders do not properly optimise their expected utilities. According to Hirshleifer and Luo (2001), overconfident investors trade aggressively both because they underestimate risk and because they overestimate the conditional expected

[12] Behavioural finance literature stresses the fact that the high trading volume observed in financial markets is perhaps the single most embarrassing fact to the standard finance paradigm and that the key behavioural factor needed to understand the trading puzzle is overconfidence (Glaser *et al*., 2003)

value from their trading strategies. Since the information they exploit is valid, their more aggressive use of it causes them to earn higher expected profits (though lower expected utility).

Furthermore, theories on overconfidence predict that high total market returns make some investors overconfident about the precision of their information (Odean, 1998b; Gervais and Odean, 2001). Although the returns are market-wide, investors can mistakenly attribute gains in wealth to their ability to pick winning stocks. Consequently, overconfident investors trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts. Alternatively, market losses reduce investor overconfidence and trading although perhaps not in a symmetric form. According to Gervais and Odean (2001), overconfidence and its principal side effect- increased trading, are likely to rise late in a bull market and fall late in a bear market. A bull market may also attract more investment capital in part because investors grow more confident in their personal investment abilities. This increase in investment capital could cause price pressures that send market prices higher.

In brief, the predictions of overconfidence models revolve around trading volume and irrational investor behaviour. Specifically, the overconfidence bias leads to increased trading volume as well as volatility in the security prices. Nevertheless, it lowers expected utilities for investors because they underestimate risk and overestimate the conditional expected value from their trading strategies. Finally, overconfidence increases as investors earn higher market returns because of the inherent self-attribution bias among individuals.

2.3 Empirical literature

2.3.1 Introduction

This sub-section provides empirical evidence relating to the index revision and overconfidence hypothesis objectives. The approach we use is to break down the empirical literature into two, namely, methodological approaches employed in the studies and empirical findings relating to all the theories reviewed. The methodological and empirical evidence for index revisions comes first and it is followed by that of the overconfidence objective.

2.3.2 Methodological approaches relating to index revisions

The event study methodology is used extensively in testing the various competing theories used to explain index effects. The pioneering studies by Harris and Gurel (1986) on the PPH, Shleifer (1986) on the ISH as well as Woolridge and Ghosh (1986) on the PPH and LCH all employed the event study methodology covering different but related periods. In this estimation technique, the identification of the event day plays an integral part in the accuracy of the analysis. In all studies, the researchers identify the date when the news of a particular event first infiltrates the market and when actual changes in the index finally become effective. In a number of studies, the announcement date differs from the date when the change in the index becomes effective. In the pioneering works, the announcement date of the addition and deletion of firms from a given index like the S&P 500 index coincides with the change date (effective date).

Following the occurrence of the event, the variables of interest are the market prices (returns) of the included (excluded) stocks as well as the trading volumes. For each event, the returns variable data are divided into an estimation period and an event window. The estimation period returns data are used to calculate the benchmark parameters and the event window period is used for computing prediction errors based on estimated parameters. The market model is the most popular model used in getting the benchmark parameters during the estimation window. The abnormal returns are represented by the prediction errors. To get the effect of the occurrence of the event (additions and deletions) one examines the abnormal returns of the affected stocks.

The Cumulative Average Abnormal Returns of the affected stocks are examined after the event takes place in order to detect any anomalies that arise. This is the case in both the pioneering studies (Shleifer, 1986; Harris and Gurel, 1986; Jain, 1987; Edmister *et al*., 1994) and in the most recent ones (Lynch and Mendenhall, 1997; Chakrabarti *et al*., 2005; Kappou *et al*., 2010). Additional procedures for detecting changes in market liquidity and abnormality in trading volume are employed as well. For example, the volume ratio testing procedure attributed to Harris and Gurel (1986) is applied in Bildik and Gulay (2008) to test for abnormal trading volume.

One challenge in establishing the IAH lies in the difficulties of empirically capturing investor awareness since there is no direct measure for it but instead reliance on proxies for investor recognition (Chen *et al*., 2004). The proxies for investors' recognition include the number of registered shareholders, the number of institutions and institutional ownership as factors to be considered in studying investor awareness. The number of shareholders before announcement of an index change is compared with the number of shareholders for the affected firm after the change date. In addition, they ascertain the number of index-fund institutional investors following index changes as well as the number and fraction of shares held by an institutional investor prior to the announcement date of the index revision and after the revision has been put in effect.

The methodologies employed in the LCH aim at defining variables that track liquidity before and after the index revisions in order to explain the permanent price increase (decrease) observed following additions to and deletions from the index respectively. Specifically, Hegde and McDermott (2003) employ the following liquidity measures; daily trade frequency, average trade size, standard deviation of order flow, proportion of crossing trades, proportion of block trades, institutional ownership and analyst coverage from the pre-addition to the post-addition period. It is because of the sophistication of the market that such information can be captured and ultimately, their study reveals a significant and long term improvement in market liquidity for S &P 500 stocks that are affected by the inclusion.

In brief, almost all studies testing the index effects employ the event study methodology. They only differ in terms of defining the duration of the event, estimation periods and defining other parameters to capture liquidity. Besides, the market model is the most popular model that is employed in the estimation window. This study follows the event study methodology but controls for thin trading problems that stock market data in developing countries suffer from.

2.3.3 Empirical evidence relating to index revisions

In almost all empirical works, the PPH is tested along with other hypotheses (Woolridge and Ghosh, 1986; Harris and Gurel, 1986; Shleifer, 1986; Edmister *et al*., 1994; Chakrabarti *et al*., 2005; Li and Sadeghi, 2009). In Harris and Gurel (1986), inclusion of a stock into the S&P 500 index earns shareholders close to 3% announcement date capital gain and it persists up to at least 10-20 trading days. This result is in line with the PPH predictions that stocks newly included into the S&P 500 index earn a significant positive abnormal return following the announcement of the inclusion although the increment is nearly fully reversed after 2 weeks. This result contrasts with that of the ISH that establishes the absence of price reversals to the pre-inclusion level share prices. Instead, there is a permanent price increase for the included stocks and this represents a new equilibrium of distribution of ownership.

Using announcement date volume and abnormal returns regression, the ISH holds since a disagreement of opinions about the value of securities among investors and analysts would lead to a downward sloping demand curve for securities (Shleifer, 1986). Both the PPH and ISH/DSDC are due to the activities of index funds as well as institutional investors. In markets where index funds are limited, the observed price pressure is due to the selling and buying activities of the institutional investors following the index revision, Pruitt and Wei (1989). Such a finding is relevant to the Kenyan market where institutional investors dominate the trading of shares and index funds are less developed. This finding is testable through the PPH.

Bildik and Gulay (2008) examine index effects of the Istanbul Stock Exchange (ISE) with a particular focus on price and trading volume of included and added stocks in the two main market indices for the period January 1995 to October 2000. What makes this study of interest to our own is that the institutional investors dominate the market and the index funds and derivative markets are not well developed just like in the Kenyan securities market yet there are significant price pressures observed. Their results of stock inclusions into (exclusions from) the ISE-30 index show that the event generates positive (negative) abnormal returns in the ISE as well as significant abnormal trading volume and volume volatility- a result that is consistent with earlier studies from developed markets. Better still, they subdivide there data set into a period when there are no index funds and derivative markets in Turkey and when index funds start developing. The pre- index funds period yields results that are weakly significant compared with the post-index funds period.

This difference in the strength of the observed price pressure that follows an index revision is because of the variation in the intensity of trade between index funds and institutional traders. In the absence of index funds (presence of a limited number of index funds), it is the institutional traders' holdings that change when there is a revision in the index. However, the price pressure exerted by the index fund managers is higher because they aim at minimising the tracking error[13]. This is the reason why the index effect results are strongly significant when index funds start operating in the Turkish market.

The deletion of stocks from the ISE-30 index affects the mean returns of the excluded stocks negatively (drop in prices) from the pre-announcement to announcement date through the change date up to the post change period. In particular, announcement and change dates consistently register losses among the excluded stocks of the ISE-30 index. The observed results on the ISE support the PPH, ISH and the attention hypothesis due to lack of index funds and derivative trading.

The distinction between the PPH and ISH lies in the fact that there is a price reversal after the change date period in the former, which is not the case with the latter. The failure of prices to revert to their pre-announcement level is because of the fact that stocks are not perfect substitutes for each other and therefore the perfectly elastic demand curve implied by the EMH does not hold. Shleifer (1986) investigates whether the demand curves for stocks are downward sloping or not. The event study methodology that Shleifer (1986) employs to study price behaviour of stocks included into the S&P 500 reveals the presence of a positive abnormal returns on the announcement of inclusion of new stocks. The positive abnormal return does not disappear for at least 10 days after inclusion. He argues that the returns are positively related to the measures of buying by index funds consistent with the hypothesis that demand curves for stocks slope downwards in the long run. A downward

[13] Tracking error is defined as the annualised standard deviation of the difference in returns between an index fund and its target index

sloping demand curve is inconsistent with the general notion of efficient markets in which stock price valuation is based on fundamental asset valuation.

The DSDC/ISH is not without challenges though. Chen *et al*. (2004) who investigate asymmetric price effects around additions to and deletions from the S&P 500 question the validity of the ISH, the information hypothesis and the trading volume-related liquidity hypothesis all of which predict a symmetric price response. Their results show that there is a significant permanent increase in the price of added firms but no permanent decline for deleted firms. Initially, the firms deleted from the index lose value but that loss is recouped in the 3 months following the deletions. This asymmetric price response is due to the changes in investor awareness that is, investor awareness can increase following a stock's inclusion but it (investor awareness) does not easily diminish when a stock is deleted from the index. The rise in investor awareness is consistent with Denis *et al*. (2003) who find that intensified monitoring makes the added firms more efficient.

Chen *et al*. (2004) test the asymmetric price effect of index revisions using the S&P 500 index data set that runs from 1976 to 2000 but subdivided into two, that is 1976-1989 and 1989-2000. Their findings indicate that the mean number of share holders increases by 831 during the 1976-1989 period and 2936 during the 1989 to 2000 period as a result of additions to the index. Thus, the change in the number of shareholders in a firm following its addition to the index is large and statistically significant. On the other hand, index deletions show that the change in the mean number of shareholders reduced insignificantly in both periods.

The fact that the number of shareholders increases following an addition to the index and diminishes somewhat following a deletion is evidence in favour of the asymmetric nature of changes in investor awareness.

Further, results indicate that the number of institutions as well as the fraction of the firm's shares held by institutions increases during both sub periods when the index is revised. During the 1976-1989 sub period, the mean number of institutions increases by 19 whereas in the 1989-2000 one, it increases by 46; all these changes are statistically significant. The mean fraction of shares held by institutions in a firm added to the index, increase significantly for both sub periods. In contrast to additions, the number of institutions holding shares falls after a firm is deleted from the S&P 500 index. When one compares the changes in institutional holdings for additions and deletions, one finds that the percentage held by institutions increases by 1.7% around additions during the 1976-1989 sub period compared with a decrease of 1.2% for deletions during the same period.

Overall, the Chen *et al*. (2004) main finding regarding the price effect around additions to and deletions from the S&P 500 index is that changes in investor awareness are asymmetric. This means that there is an increased awareness for added stocks as investors learn about them but a smaller drop in awareness for deleted stocks.

In another study that contests the assumption that index revisions carry no information, Dhillon and Johnson (1991) re-examine the PPH and ISH of Harris and Gurel (1986) and

Shleifer (1986) using stocks, bonds and options data. They mainly examine stocks added to the S&P 500 for the period 1978-1988, traded options on stocks being added and straight bonds of companies added. Their findings show that the announcement effects documented by Harris and Gurel (1986) and Shleifer (1986) are still present in the 1984-1988 stocks. Besides, the stock prices do not re-adjust to their preannouncement levels even when the study period is extended to 60 days.

Dhillon and Johnson (1991) further argue that even when they prolong the Harris and Gurel (1986) post announcement period for added stocks their prices continue to decline and this is attributed to problems of risk adjustment and not a mere reversal of a price rise induced by price pressure. They present call and put option returns for traded options on stocks affected by the revision of the S&P 500. There is a very strong reaction on the change date with almost all call prices increasing whereas the puts decline. In addition, the bond prices for companies being included in the S&P 500 also increase on the announcement date. Finally, an examination of the mean volume ratio of trading volume following an announcement indicates a permanent increase in the trading volume, which means that the observed price pressure is due to increased liquidity in the market.

Dhillon and Johnson (1991) conclude that stocks, bonds and calls for firms being added to the S&P 500 have price increases on the announcement date, while put prices decline. Stock prices do not return to the preannouncement level in the post-1983 sample. Accordingly, their evidence points towards the information hypothesis.

2.3.4 Methodological approaches relating to the overconfidence hypothesis

Glaser *et al*. (2003) offer a general framework that gives rise to two channels that one can use in estimating behavioural finance models in general and overconfidence in particular. The first channel involves estimating predictions concerning trading behaviour and investment performance of (individual and institutional) investors and the second one is the estimation of predictions concerning market outcomes. It is the first category of estimation that interests our overconfidence hypothesis that mainly predicts that trading volume increases with an increase in the degree of overconfidence. Thus, the empirical means of testing for overconfidence include the following: (i) analysing market- level data such as returns and trading volume and (ii) analysing trading behaviour of investors as well as correlating proxies of overconfidence with economic variables such as trading volume.

Studies that employ market-level data to estimate overconfidence include- Statman *et al*. (2006), Chuang and Lee (2006), Kim and Nofsinger (2007) and Chuang *et al*. (2010). Statman *et al*. (2006) use the US market-level data to study investor overconfidence and trading volume behaviour. Specifically, they employ monthly observations of trading volume and stock returns for common stocks of the New York Stock Exchange (NYSE) for the period of August 1962 to December 2002. They follow Lo and Wang's (2000) proxy of trading activity as share turnover (shares traded divided by outstanding shares) and aggregate security turnover measured on a value-weighted rather than an equal-weighted basis. Since the turnover series contain a secular trend, it means that it is non-stationary. The Hodrik and

Prescott (1980) algorithm is employed in the detrending process that aims at achieving stationarity in the turnover series.

In order to test the overconfidence predictions, Statman *et al*. (2006) employ a Vector Auto Regression (VAR) estimation technique and its associated impulse response functions on turnover series and return time series for both market and individual securities. They employ the Schwartz Information Criteria to determine the optimal monthly lag structures. The VAR formulations contain lagged values of detrended turnover series and lagged market-wide returns in addition to other control variables of market volatility and dispersion used to control for alternative factors accounting for trading activity. The study aims to test distinct implications associated with changes in trading volume over time for both market and individual securities that are motivated by overconfidence theories.

The methodology in Statman *et al*. (2006) does a commendable job in capturing overconfidence bias in market-level data. Its main shortcoming is the way it deals with the secular trend in the turnover series when it employs the Hodrick-Prescott filter to smooth the trend. Harvey and Jaeger (1993) critique this form of filter because it induces spurious cycles in the data that affect subsequent regression analysis. Further, the study's use of monthly data other than higher frequency data in analysing stock market phenomena is not likely to present the best results.

Chuang and Lee (2006) and Chuang *et al*. (2010) directly test overconfidence hypotheses in two related works. Chuang and Lee (2006) test four hypotheses relating to overconfidence by examining market-level data on the NYSE and the AMEX for the period of January 1963 to December 2001. The stocks used in the study have data relating to stock prices, trading volume and market capitalisation. Again, just like in Statman *et al*. (2006), Chuang and Lee (2006) use turnover series as a measure of trading activity in addition to employing two different measures of detrending the turnover series.

To test whether overconfident investors overreact to private information and under react to public information one needs to identify private and public information. It is for this reason that Chuang and Lee (2006) employ a structural VAR model in which the identification of private and public information depends on theoretical considerations.

Chuang and Lee's (2006) second hypothesis test of whether market gains (losses) make overconfident investors trade more(less) aggressively in subsequent periods employs a bivariate Granger causality test in order to establish the causal relations between trading volume and market returns. The bivariate Granger causality regressions estimated through a Seemingly Unrelated Regression (SUR) technique contain lagged values of detrended turnover, market returns as well as control variables such as the mean absolute cross-section returns deviation and absolute market returns. To confirm the dynamic nature of overconfidence through biased self-attribution, Generalised Autoregressive Conditional Heteroskedasticity (GARCH)-type of models are employed.

The hypothesis that excessive trading by overconfident investors contributes to excessive volatility is tested through a decomposition of trading volume series into two. These are- trading volume associated with overconfidence and trading volume associated with other factors other than overconfidence. The purpose of the decomposition is to yield the two forms of trading volume that are used in the augmentation of the GARCH models in order to aid in the differentiation of excessive trading of overconfident investors from other factors that lead to market volatility. Put differently, the two components of trading volume show that one component of trading volume relates to past stock returns and the other component is unrelated to past stock returns.

The fourth and last hypothesis of Chuang and Lee's study tests whether overconfident investors underestimate risk and trade more in riskier securities. This is achieved through the construction of portfolios with varying risk levels. The two measures of risk employed are return volatility and firm-specific risk. A joint estimation of two portfolios that is, one composed of riskiest securities and the other composed of least risky securities is conducted through a SUR procedure.

The study by Chuang *et al*. (2010) tests the overconfidence hypothesis among Asian investors across nine stock markets in Asia. Specifically, they investigate whether both domestic and U.S. market gains make Asian investors trade more aggressively in subsequent periods in their domestic markets. Weekly returns and trading volume series are constructed for the period of January 1995 to June 2010 in order to run a multivariate seemingly unrelated regression model that is employed throughout the study. The methodology that Chuang *et al*. (2010) follow is a slight modification of one used in Chuang and Lee (2006).

The study by Kim and Nofsinger (2007) is another kind that employs monthly returns on the Tokyo Stock Price Index (TOPIX), annual individual investor share-ownership and financial statement data for Japanese stocks to study investor behaviour during bull and bear markets. There are two estimation techniques employed in the study above. The first one involves the creation of several portfolios that are analysed based on ownership level whereas the second approach uses pooled ordinary square regressions in which the dependent variable is the level of ownership with a series of independent variables that include a dummy for a bear or bull market, volatility, beta, book-to-market value and abnormal returns.

The second alternative to estimating overconfidence models involves the analysis of individual behaviour of investor data sets as well as correlating overconfidence proxies with other economic variables. Vivid examples of studies in this category include Odean (1999), Barber and Odean (2001) and Chen *et al*. (2007) and studies that employ individual information of investors holding accounts with discount brokerage houses. Another example on the NSE that uses data on institutional traders' behaviour is by Waweru *et al*. (2008).

Odean (1999) employs data of an undisclosed discount brokerage house in the US that involves the analysis of 10,000 customer accounts for the period of January 1987 to

December 1993. The study aims to establish whether the trading profits of the account holders are sufficient to cover their trading costs. This is achieved through the examination of returns horizons of four months (84 trading days), one year (252 trading days) and two years (504 trading days) following a transaction. In a related study by Barber and Odean (2001), monthly portfolio returns for 37,664 households are estimated for the period of February 1991 to December 1996. Since the study is interested in the gender differential earnings, both average gross and net monthly returns earned by both men and women are estimated. The gender differential earnings are used to proxy overconfidence. In addition, each household's monthly portfolio turnover is estimated. Benchmark abnormal returns are constructed for the purposes of comparing monthly abnormal return differentials across the sexes. Security selection ability between men and women is carried out by comparing returns of stocks bought with those sold.

The Odean (1999) methodology is able to illuminate the overconfidence bias in a micro-level perspective. This is so because it captures household investment decisions in US stock markets. The psychological biases inherent in these decisions are better captured in this approach than using the aggregate market-level approach. However, its major challenge lies in the difficulties in accessing the kind of data it uses.

The study by Chen *et al*. (2007) involves an investigation of three behavioural biases inherent in emerging market investors, particularly the Chinese investors that serve as a case study. They investigate the disposition effect, the representativeness bias and the overconfidence hypothesis by employing 46,969 individual investor accounts and 212 institutional investor accounts held at a large brokerage firm in China for the sample period of May 20, 1998 to September 30, 2002. The empirical methodology employed to establish overconfidence (which is proxied by frequency of trading) largely follows that of Barber and Odean (2001) in which the mean monthly portfolio turnover for each brokerage account is estimated. Further, since overconfident traders are assumed to possess under diversified portfolios, the mean number of stocks in each account is examined. Similarly, each account's mean market-adjusted returns are measured to assess the performance of the investors' portfolios. And finally regression analysis that employs overconfidence metrics is applied. The dependent variables include- the number of stocks held, turnover and portfolio returns whereas the personal characteristics of investors (account age, investor's age, frequency of trading dummy, account value and a location dummy) constitute the independent variables.

The study by Waweru *et al*. (2008) investigates the role of behavioural finance and investor psychology in investment decision-making among institutional investors operating at the NSE. They employ survey data methodologies to study the trading behaviour of 23 institutional investors dealing in securities listed on the NSE. Specifically, factor analysis is conducted to test the reliability of the items in the multi-item scales used in ranking a number of factors. Behavioural finance theories are employed in the choice of the factors that are ranked by the respondents. The behavioural factors investigated include a number of heuristics such as representativeness, availability bias, overconfidence, mental accounting, regret aversion and the like. However, the methodology employed does not use any rigorous econometric approaches to support its findings.

In summary, two salient issues crop up in the methodologies employed in estimating behavioural finance theories. First, market-level data is applicable in scenarios where the data points are enormous since this permits the transformation of the data sets into monthly or weekly time series for meaningful econometric analysis. Second, all studies that employ data sets from discount brokerage houses choose not to disclose the specific names of the brokerage firms. Much as this does not affect their analysis, it is a pointer to the difficulties or impossibilities involved in sourcing this kind of data most especially in emerging and frontier markets in Africa. The argument that investor behaviour is deductible from aggregate-level data justifies the approach of subjecting stock market-level data to time series econometric analysis.

2.3.5 Empirical evidence relating to the overconfidence hypothesis

The Statman *et al*. (2006) study that investigates overconfidence and trading volume has three major empirical findings. First, there is a positive and highly significant association between market turnover and market returns. In other words, there is a statistically significant tendency for market-wide turnover to increase in the months following high market returns, after accounting for contemporaneous and lagged volatility associations- an observation that is consistent with overconfidence predictions. The disposition effect however, can also produce similar results hence in order to distinguish between the two theories (overconfidence and disposition effect); they employ the VAR and impulse response functions on the returns time series on individual stocks.

Second, security turnover levels are responsive to past market returns even when past security returns are included in the VAR model. This result helps in the discrimination between overconfidence and the disposition effect. Specifically, individual security turnover is positively related to both lagged security returns and lagged market returns. The positive security turnover response to own lagged return would correspond with the disposition effect while the positive turnover response to lagged market returns is evidence of changes in investor overconfidence.

The third and final finding is that the lead-lag relationship between returns and turnover is stronger in small capitalisation stocks and in earlier periods, perhaps due to the relatively larger role of individual versus institutional investors in the small capitalisation stocks. This observation applies to both the disposition effect and overconfidence hypothesis though.

The study of Chuang and Lee (2006) tests four hypotheses on overconfidence among the US investors and all of which are found to hold. The first study result lends support to the assertion that overconfident investors overreact to private information and under react to public information. The dynamic effects of private and public information shocks on stock prices indicate that with an initial under reaction, stock prices overreact to private information followed by a correction process and under react to public information reaching an equilibrium response without a significant long-run reversal.

The Granger-causality tests on stock returns and turnover indicate that high stock returns significantly Granger-cause high trading volume (turnover) and there is no feedback effect. This result is also found in other studies that are not necessarily testing for over confidence hence a further test for biased self-attribution is conducted to prove if overconfidence is in existence. To study investors' reactions to market gains when they make right and wrong forecasts and to the precision of their forecast errors, the GARCH specifications are made use of. The study reveals that investors become overconfident and trade more actively following market gains, as they make right forecasts of future stock returns than as they make wrong forecasts. In addition, there is weak evidence that investors trade more actively when their forecast errors are smaller; these findings are a confirmation of the biased self-attribution prediction.

Chuang and Lee (2006) also report that conditional volatility is positively accounted for by trading volume that relates with past returns. This provides empirical support to the hypothesis that if investors are overconfident; their excessive trading in securities markets contributes to excessive volatility. Finally, investors trade more in riskier securities whose volume impact becomes higher with more trading by overconfident investors.

The Chuang and Lee (2006) study is related at least methodologically to that one of Chuang *et al*. (2010) that examines Asian investors' overconfidence behaviour across nine stock markets as well as their behaviour in the US markets. Consistent with the predictions of the overconfidence theory, results indicate that domestic (US) market gains make most (some) Asian investors to trade with more overconfidence in bull markets, in high volatility market states and in extremely high market return periods- a result that is partially evidenced in Chuang and Lee (2006) among US markets. Events in the US influence market outcomes in Asia because of the high integration of markets between the two regions. A comparison of overconfidence levels across markets reveals that markets with short-sales constraints exhibit a higher level of overconfidence among its traders than markets with no short-sale constraints.

Kim and Nofsinger (2007) present mixed results regarding the behaviour of Japanese investors during bull and bear markets. Their study aims at testing individuals' attitudes and preferences toward stock risk, book-to-market valuation and past returns in different market conditions as well as assessing individuals' investment performance. The individual risk preference results reveal that individuals have a tendency to hold high-risk stocks but these tendencies only appear during a bear market. Overconfidence theories predict high-risk taking behaviour in bull markets because individuals confuse high returns they earn with their own abilities to picking winning stocks. Hence, the Kim and Nofsinger (2007) findings contradict the overconfidence hypothesis predictions in Chuang and Lee (2006) and Chuang *et al*. (2010) studies.

Furthermore, there is a strong and distinct relationship between book-to-market and the stock's level of individual investor ownership but only during bull markets. This strong and positive relationship between book-to-market and individual ownership is consistent with the hypothesis that Japanese individual investors are overconfident during bull markets and that their overconfidence is estimable from the aggregate market data.

Japanese investors have a greater tendency of buying past winners during a bull market (but not selling past losers) as compared to the bear market. Further, poor trading decisions occur during a bull market situation hence the findings are consistent with the hypothesis that individuals suffer more from an overconfidence bias during bull markets. The study further indicates that with each continuing bullish (bearish) year, investors tend to positively (negatively) feedback trade more than they did the prior year. Overconfidence trading theories predict a positive feedback trading and poor performance.

There is a similarity in the findings of Odean (1999) and those of Barber and Odean (2001). They both report significant excessive trading that reduces the wealth of those investors that engage in it. Specifically, Odean (1999) finds that traders in his survey display excessive trading that reduces their returns; the genesis of their excessive trading is the inherent psychological bias of overconfidence. These overconfident traders may transact business even when their expected gains are not enough to offset their trading costs. Barber and Odean (2001) studies overconfidence along gender dimensions and discovers that men trade more than women do. The portfolio turnover results indicate that women turn their portfolios over approximately 53% annually (monthly turnover 4.4% times twelve); while men turn their portfolios over approximately 77% annually (monthly turnover 6.4% times twelve). Hence, those who trade the most (men) earn lower returns compared to women. Overall, Barber and Odean (2001) results are consistent with overconfidence predictions.

The Chen *et al*. (2007) study that tests a variety of psychological biases in emerging China confirms the presence of the disposition effect, representativeness and overconfidence biases in individual and institutional investors. Both groups of investors appear to be trading frequently, an exercise that reduces their abnormal returns. Nevertheless, in comparative terms since institutional investors own more stocks than the individual investors do, they trade more frequently and actually earn more. This result contradicts Odean (1999) and Barber and Odean (2001) that find reduced earnings for those investors that trade the most. Investors who have been in the market longest (measured by age of investor account), exhibit high frequent trading as well as better returns. Evidence suggests that when experience makes investors overconfident, the overconfidence seems to be justified ex post as the overconfident investors earn higher returns.

The only study involving the NSE by Waweru *et al*. (2008) reveals a number of heuristics within the investment decisions of institutional investors operating at the exchange. Specifically, 76% of the institutional investors apply heuristics in their investment decisions. Almost all (96%) of investors are driven by the availability bias and therefore place undue weight on easily available information when making investment decisions. Another heuristic indicator that is of interest to this particular study is that of overconfidence (use of predictive skills to time and outperform the market) and it is exhibited by 69% of institutional investors at the NSE. Such a finding underscores the fact that overconfidence is by no means limited to individual investors but to institutional investors as well.

Generally, empirical evidence on the overconfidence bias reveals that the analysis of trading volume behaviour assists in detecting anomalous behaviour particularly at the aggregate level. This is so because most overconfidence predictions that involve excess trading, excess risk taking and excess volatility are tested through the examination of volume and returns (Chuang and Lee, 2006; Statman *et al*., 2006; Chuang *et al*., 2010). It is the combination of the interaction of volume (turnover), market returns and individual security returns that helps in sieving out the overconfidence bias in market-level data. In both developed and emerging markets, behavioural biases affect market outcomes as evidenced in the reviewed studies. In the presence of individual-specific data the frequency of trading of individuals is crucial in identifying which particular investors are overconfident. This is what Odean (1999), Barberis and Odean (2001) and Chen *et al*. (2007) strive to show in their works. Finally, a number of behavioural biases are inherent in the investment decisions of institutional investors operating in the Kenyan and Chinese securities markets, Waweru *et al*. (2008) and Chen *et al*. (2007).

2.4 A synthesis of the reviewed literature on behavioural finance

The literature we have presented revolves around the two pillars of behavioural finance which are the limits-to-arbitrage and psychology. The former aims at showing persistent deviations from the EMH whereas the latter aims at depicting how investor behavioural biases affect returns and volume in the market. The revision of stock market indices shows lasting price and volume effects synonymous with deviations from EMH whereas the overconfidence bias portrays the individual behaviour in market-level data.

The literature survey on index effect theories reveals that there are broadly two theoretical perspectives: (i) demand-based and (ii) information-based explanations. The main premise of the demand-based explanation is that index revisions are information-free events (Li and Sadeghi, 2009). For example, Shleifer (1986) is able to employ a downward sloping demand curve to show that the price effect following an index revision is due to the demand from index tracking. The price effect could be either permanent or temporary. Harris and Gurel (1986) assert that the temporary effect is attributed to the PPH predictions of price reversals in the long-run while the permanent effect is due to the ISH predictions of absence of price reversals since the new price reflects changes in the distribution of security holdings in equilibrium (Lynch and Mendenhall, 1997; Wurgler and Zhuravskaya, 2002). More importantly is that both the PPH and ISH results are inconsistent with the EMH.

On the other hand, the main premise of the information-based explanations is that the revision of a widely followed index is not an information-free event. Information-based theories include the ICH and the liquidity hypothesis. Studies in support of the ICH reveal that addition of a stock to the index conveys favourable news about the firm's future prospects; it is for this reason that a permanent price increase is observed following stock additions (Jain, 1987; Dhillon and Johnson, 1991). For the liquidity hypothesis, the price increase following index additions is due to increased liquidity arising from greater visibility of the added stock, greater interest from institutional investors, higher trading volume and lower bid-ask spreads (Amihud and Mendelson, 1986; Hegde and McDermott, 2003). In addition, Harris and Gurel (1986) find increased liquidity following S&P 500 index additions while deletions reduce liquidity.

The attention hypothesis is the only theory so far that portrays the asymmetric behaviour of index revisions, that is to say there is an asymmetric response in excess returns following additions to (deletions from) a given index. Almost all the theories assume that price responses to index revisions are always symmetric that is to say, observation of positive abnormal returns for index additions and negative abnormal returns for deletions. According to Merton (1987), index additions can increase the recognition of a firm leading to increase in its value as investors use it to construct their optimal portfolios. Nevertheless, index deletions are not necessarily accompanied by reduced recognition. The asymmetric price effects in the attention hypothesis are attributed to variations in the awareness of investors concerning the stocks added to (deleted from) the index. Specifically, index additions can potentially lead to increased investor awareness due to enhanced monitoring and reduction in the information asymmetry component of the bid-ask spread while index deletions do not necessarily prompt a reduction in investor awareness that yields negative abnormal returns.

Generally, the evidence of positive significant returns on the day that a stock is introduced into a given market index signals a profit opportunity and the reverse is true. The literature shows that this is the case in the developed markets in the US and the Asian countries where the majority of previous studies are focused. We pointed out in chapter one and appendix Tables 1.1 and 1.3 that developed markets and frontier markets are structurally and by extension operationally different. It is against this background that we choose the NSE- a frontier market to test the index effects in order to study the behaviour of securities returns following index revisions.

With these theories on the one hand and the NSE which is the focus of this study on the other, one would be left with the task of investigating which theories are most likely to apply to this market when the market index is reviewed. The criteria for selecting the stocks to include or drop from the NSE-20 share index are within the public domain. It would therefore seem reasonable an argument that the NSE-20 share revisions carry no new information about the affected securities since the criteria used is known to all market participants. This argument would render the information-based theories of stock revisions in the case of NSE inappropriate.

Further, since the attention hypothesis is premised on wide media coverage for its results to hold, its hard a task to determine if the revisions are given wider coverage in the media. So far, the most feasible theories that can be easily tested are the demand-based theories that simply examine the prices of the stocks over a relatively shorter time period (the PPH) or over a relatively longer time period (ISH). The event study methodology is applied in the testing of all these theories since the interest is in establishing abnormal returns arising when the index revision event takes place.

The literature survey conducted also reviewed another pillar of behavioural finance called psychology. One difficulty of estimating psychological biases in finance lies in the fact that it is only a few biases that are traceable in the market-level data. The reviewed literature on psychology zeroes in on the overconfidence bias because its theoretical underpinnings relate to observable market features such as trading volume, risk-taking and volatility. Throughout the overconfidence literature, it is evident that overconfidence increases with volume, risk-taking and volatility in different market settings.

It is evident that investors in developed markets depict the cognitive bias of overconfidence in their investment decisions. This bias results into a situation in which high market returns Granger cause turnover (trading volume). The investors' overconfidence increases as their predictions or forecasts of market returns coincide with the actual returns (the biased self attribution case). Subsequently, markets in which overconfident investors operate depict high trading volumes and increased conditional volatility.

Studies employing individual data reveal that investors who depict traits of overconfidence inadvertently engage in excessive trading that reduces their wealth. Surprisingly, overconfident investors may transact business even when their expected gains are not enough to offset their trading costs. Gender-wise overconfidence studies reveal that men trade more than women do and as such the former earn less than the latter.

Institutional traders also depict biases in their trading just like individual traders; specifically their frequent trading is synonymous with the overconfidence predictions. Further, there are other psychological biases such as the disposition effect, availability and the representativeness heuristics that show up in the decisions of institutional investors in the emerging market of China and in Africa's frontier market of NSE.

The challenge in the studies relating to overconfidence predictions is that there are extant theories whose predictions do not differ from those of overconfidence in the aggregate market. As such, the ideal approach is to use individual-specific data sets where it is easier to trace the actual investors or individuals that are overconfident. Odean (1999), Barber and Odean (2001) find that individual investors appear overconfident about their perceived information and ability to trade so do institutional investors in Chen *et al*. (2007). Nevertheless, Fama (1998) argues that a valid finance theory should be able to explain the market as a whole rather than a specific type or group of investors.

Just like in the case of index revisions, studies on overconfidence bias are based on developed stock markets such as the NYSE, AMEX and the Japanese one. Others are based on emerging markets in China, Singapore and Hong Kong whose market features are different from those in frontier markets in Africa (see Appendix Tables 1.1 and 1.3).

Specifically, developed markets have highly efficient equities, foreign exchange and derivative markets, permit stock lending, short selling and off-exchange transactions that are highly unlikely in frontier markets. In effect, there is a higher liquidity in developed markets that supports global investment than is the case with frontier markets.

The fact that differences exist in terms of the liquidity, efficiency, market sophistication, form of regulation and type of investors between the developed and the frontier markets, one would expect this difference to be passed on to the empirical findings regarding psychology. However, the same psychological biases inherent in investor biases in developed markets surface in frontier markets as is shown in Waweru *et al*. (2008).

In general, behavioural finance theories follow its two building blocks of limits-to-arbitrage and psychology. Empirically, various theories have been tested in developed markets and they have been found to hold. The fact that developed markets are different in terms of their structures and operations would mean that using results from the developed markets to explain phenomena in frontier markets would be inappropriate. It is for this reason that we seek to test these theories (behavioural finance) in NSE so that we can make a generalisation on frontier markets.

2.5 The theoretical framework for testing behavioural finance hypotheses at the NSE

In testing behavioural finance hypotheses on the NSE the study follows the two pillars of psychology (overconfidence hypothesis) and the limits-to-arbitrage (index revisions). On the one hand, the premise of investor overconfidence emanates from a large body of evidence from cognitive psychological experiments and surveys depicting individuals or groups of individuals as overestimating their own abilities in various contexts. On the other hand, index effects emanate from index revisions and there by producing market returns that are inconsistent with the EMH.

The theoretical framework guiding the overconfidence objective heavily relies on Daniel *et al*. (1998) for it combines private and public information signals in the analysis of overconfident investors. In this framework, unlike in others, one is able to capture both the static and dynamic nature of the overconfidence bias. The variation in overconfidence (or the dynamic component) depicts the changes in the levels of confidence as individuals make their trading decisions. Cognitive psychological experimental evidence supports the observation that individuals update their beliefs about given phenomena by crediting themselves for favourable outcomes and blaming external factors for unfavourable outcomes -the self-attribution bias. Hirshleifer (2001) asserts that overconfidence and biased self-attribution are static and dynamic counterparts.

For index revisions, since we opt to for demand based theories other than information-content ones because the criteria governing revisions at the NSE are always in the public domain[14] and consequently revisions do not carry fundamental news about the affected securities. Besides, in relatively small markets like emerging and pre-emerging cases with

[14] Refer to NSE (2007) Ground Rules NSE 20 Share Index Recommendations, NSE policy document.

fewer securities traded like the NSE, it is highly unlikely that index revisions can be interpreted as transmitting quality signals because the market participants are aware of these firms' prospects even before the revisions (Shankar and Randhawa, 2006).

The demand-based theories governing the theoretical framework for index revisions considered in this study are the PPH and ISH. The PPH predicts that additions to (deletions from) a given index increase (decrease) the prices of the affected stocks. However, after two weeks of trading the changes are fully reversed. In essence, the PPH predicts only temporary changes in the abnormal returns. The ISH on its part also predicts that additions to (deletions from) the index increase (decrease) the prices of the affected stocks; however, the change in price is permanent. Both results of the PPH and the ISH violate the predictions of efficient markets.

In summary, this study's test of behavioural finance theories strives to follow its two pillars-psychology and limits-to-arbitrage. The overconfidence bias follows Daniel *et al.* (1998) theories of static and dynamic confidence while the index revision theories are the PPH and ISH pioneered in Scholes (1972) and first empirically tested in Harris and Gurel (1986) and Shleifer (1986).

2.6 Hypotheses drawn from the literature

The following are the key hypotheses that we draw from the reviewed literature:

(i) Index revisions are sources of EMH violations

(ii) Higher levels of overconfidence amongst investors lead to higher trading volumes.

We ask the following research questions in testing the above hypotheses[15]:

(i) Do revisions of the NSE-20 share index depict violations of the EMH?

(ii) Which index revision theories best capture the price behaviour of the NSE stocks after revisions in the main share index?

(iii) How does one deal with the trends in the trading volume series of the NSE?

(iv) What is the causal relationship between trading volume and stock returns of the NSE?

(v) Does the overconfidence bias among traders at the NSE lead to market volatility?

(vi) How do higher market returns (losses) affect investors' trading behaviour in the subsequent period?

[15] The first two research questions are used in investigating the hypothesis on index revision whereas the last four are employed in the investigation of the hypothesis on investor overconfidence.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The goal of this chapter is to lay out the econometric models and issues that we use in the estimation exercise. First, we specify the overconfidence models followed by a description of the data used as well as illustrating the procedures for generating returns and turnover. We also describe the procedure of dealing with the time trend in the turnover series. Second, we illustrate the event study methodology to test index revisions at the NSE.

3.2 The econometric models for Overconfidence bias

3.2.1 Static Overconfidence

Daniel *et al*. (1998); Gervais and Odean (2001); Glaser *et al.* (2003); and Biais *et al*. (2005), hypothesize that if investors are overconfident, they attribute market gains to their own ability to picking winning stocks and trade more aggressively in the subsequent periods. The overconfidence hypothesis predicts a causality running from stock returns to trading volume.

To estimate the occurrence of static overconfidence in the NSE market data we test for causality of the Granger type. We specify the Chuang and Lee (2006) estimation procedure of Granger (1969, 1988) in order to test Granger- causality between trading volume and stock returns[16].

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[16] Chuang and Lee's (2006) original specification includes extra variables such as the absolute value of the market return $|r_t|$ and the mean absolute cross-sectional return deviation MAD_t as information flow proxies (market and firm-specific). These variables have a positive insignificant relationship with trading volume in

(3.1)
$$v_t = \alpha_{11} + \sum_{j=1}^{P} \beta_{11j} v_{t-j} + \sum_{j=1}^{P} \beta_{12j} r_{t-j} + \varepsilon_{1t}$$
$$r_t = \alpha_{21} + \sum_{j=1}^{P} \beta_{21j} v_{t-j} + \sum_{j=1}^{P} \beta_{22j} r_{t-j} + \varepsilon_{2t}$$

where v_t is the detrended trading volume, and r_t is the market return (market-wide return). We employ the Akaike Information Criterion (AIC), and Schwartz Bayesian Criterion (BIC) to determine the number of lags *p* in regression equation 3.1.

We estimate the relation in 3.1 as a seemingly unrelated regression (SUR) system due to two main reasons. First, there are efficiency gains in estimation when one combines information in each equation into one system and second, one is able to impose and test restrictions involving parameters from each equation.

The empirical prediction in 3.1 is based on the null hypothesis that stock returns do not Granger-cause trading volume. The rejection of the null hypothesis that stock returns do not Granger-cause trading volume ($H_0 : \beta_{12j} = 0$, for all j) provides evidence in favour of the hypothesis that market gains (losses) make overconfident investors trade more (less) aggressively in subsequent periods. Since volume is not a fundamental variable of the firm, rejection of the null hypothesis that trading volume does not Granger-cause stock returns ($H_0 : \beta_{21j} = 0$, for all j) is evidence for market inefficiency. Lastly, if we find a positive

a number of studies (Karpoff, 1987 and Bessembinder *et al*., 1996) hence we dropped them from our regressions.

feedback relation between stock returns and trading volume, it provides evidence in favour of the sequential information arrival or positive-feedback trading hypothesis.

3.2.2 Dynamic or Outcome-dependent overconfidence/ biased self-attribution

Chuang and Lee (2006) hypothesize that if self-attribution bias causes investors to learn to be overconfident; the extent to which concurrent trading volume is positively correlated with past stock returns conditional on investors' right forecasts is greater than that conditional on their wrong forecasts.

To investigate if self-attribution bias is inherent in the trading behaviour of the NSE investors, we relate the market's trading volume and stock returns conditional on the investors' forecasts. We make use of the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) class of models in order to decompose stock returns into expected and unexpected returns to enable us relate trading volume and returns in a single regression.

3.2.2.1 Specification of the GARCH models

Finance literature is replete with volatility in asset returns behaviour. The majority of studies in this direction make use of the generalised autoregressive conditional heteroskedasticity models to model volatility. The first model that provides a systematic framework for modelling volatility is the Autoregressive Conditional Heteroskedasticity (ARCH) of Engle (1982) which we formulate in equation 3.2.

(3.2)
$$r_t = \mu_t + \eta_t \quad , \eta_t \sim N(0, h_t)$$
$$h_t = \omega + \sum_{j=1}^{q} f_j \eta_{t-j}^2 .$$

where $\omega > 0$, $f_j \geq 0$, $j = 1, ..., q-1$ and $f_q > 0$. The parameter restrictions form a necessary and sufficient condition for positivity of the conditional variance h_t[17]. r_t depicts the logarithm return on the market at time t, μ_t is the mean of the market return conditional on past information and η_t is the innovation or shock of the market return at time t. The returns equation represents the conditional mean that describes the evolution of the dependent variable over time. The conditional variance equation depicted in equation (3.2) defines an ARCH model of order q.

The major concern of conditional heteroskedastic models is the evolution of the conditional variance (h_t) and the manner in which it evolves over time distinguishes one volatility model from another (Tsay, 2005). Further, the basic idea of ARCH models is that (i) a shock η_t of an asset return is serially uncorrelated but dependent and (ii) the dependence of the shock η_t can be described by a simple quadratic function of its lagged values as illustrated in equation (3.2) (Tsay, 2005).

Much as the ARCH model is the foundation of all the other ARCH family extensions, it has some weaknesses. Its main weakness is that it often requires many parameters to describe

---

[17] The conditional variance term h_t is also denoted as σ_t^2 in econometric literature, for consistence purposes we use the former notation.

the volatility process of an asset's return (Tsay, 2005). The requirement of too many parameters comes at a cost- the non-negativity constraints might collapse. Independently of each other, Bollerslev (1986) and Taylor (1986) developed a more flexible generalisation of the ARCH approach, the GARCH model whose formulation is more flexible than Engle's (1982) formulation. They additionally included p lagged values of the conditional variance into Engle's original ARCH to yield a GARCH (p , q) process as indicated in equation (3.3).

$$(3.3) \quad h_t = \omega + \sum_{j=1}^{q} f_j \eta_{t-j}^2 + \sum_{k=1}^{p} f_k h_{t-k} \, ,$$

where $\omega > 0$, $f_j \geq 0$, $f_k \geq 0$, $\sum_{i=1}^{\max(p,q)} (f_{ji} + f_{ki}) < 1$, f_j and f_k are the ARCH and GARCH parameters respectively.

The conditional variance defined in equation (3.3) above has the property that the unconditional autocorrelation function of η_t^2, if it exists, can decay slowly, albeit still exponentially (Terasvirta, 2006). For the ARCH family, the decay rate is too rapid compared to what is typically observed in financial time series, unless the maximum lag q in the ARCH model in equation (3.2) is long. Further, the conditional variance equation in (3.3) is a more parsimonious model than a higher order ARCH and as a result, most users prefer it to the simpler ARCH alternative. Additionally, the GARCH (p,q) models allow the parsimonious parameterisation for conditional variances in the same way as ARMA (p,q) models for conditional means.

The GARCH (1, 1) model that is $p = q = 1$ in equation (3.3) is the main workhorse in almost all applied financial economics whenever conditional heteroskedasticity is a problem (Schwaiger, 1995; Duan, 1997; Tsay, 2005; Lim *et al*., 2005; Terasvirta, 2006; Kramer and Azamo, 2007; Kirchgassner and Wolters, 2007). Besides, Brooks (1996) asserts that it is highly unlikely that a GARCH model of order greater than one in the autoregressive and moving average components would be required owing to the fact that a GARCH(1,1) model implies an infinitely long memory with respect to past innovations.

The biggest challenge of the GARCH (1, 1) model is its uniform treatment of positive and negative shocks, that is, they (both positive and negative shocks) exert the same impact on conditional variance as the signs disappear due to squaring. What this means is that the GARCH (1, 1) model does not account for skewness or asymmetry associated with a distribution. Finance literature shows that the reaction of volatility of share prices is different if the shocks are negative that is, if they result from bad news than if, they are positive, that is if they result from good news. This “leverage effect” leads to higher volatility as a result of negative shocks as compared to positive ones.

For purposes of robustness the study employs two forms of GARCH-type extensions in order to capture the asymmetric response of volatility of share prices of the NSE to negative and positive shocks. Besides, these GARCH extensions enable us to decompose stock returns into expected and unexpected returns that have a bearing on investor behaviour in the overconfidence sense. These extensions are Nelson's (1991) Exponential GARCH (EGARCH) and Glosten *et al*. (1993) GJR- GARCH.

The choice of these specifications lies in the fact that financial markets data is infested with outliers that make it incompatible with normal distribution assumptions and besides, volatility clustering behaviour is evident in several cases. Such behaviour, gives rise to leptokurtic distributions that exhibit more mass at the centre and at the tails of the distribution (Mandelbrot, 1963; Harrison and Paton, 2004; and Kirchgassner and Wolters, 2007). In the case of NSE, Obere (2009) finds evidence of leptokurtic distributions in ordinary share returns, volatility clustering feature as well as asymmetry in the daily returns. The EGARCH and GJR-GARCH are appropriate with such market characteristics of the NSE.

We employ Nelson's (1991) Exponential GARCH (EGARCH) model given in equation 3.4.

$$\begin{aligned} & r_t = \mu_t + \eta_t, \\ (3.4) \quad & \eta_t \mid (\eta_{t-1}, \eta_{t-2}, \ldots., r_{t-1}, r_{t-2}, \ldots) \sim GED(0, h_t), \\ & \ln h_t = \omega + f_1 \left(\frac{|\eta_{t-1}| + \kappa \eta_{t-1}}{\sqrt{h_{t-1}}} \right) + f_2 \ln h_{t-1}, \end{aligned}$$

where r_t is the weekly market return in its natural logarithmic form, μ_t is the mean of the market return (r_t) conditional on past information, and h_t is the conditional volatility. The volatility parameter κ captures the asymmetric effect in the EGARCH model. For $\kappa < 0$, negative shocks will obviously have a bigger impact on future volatility than positive shocks of the same magnitude. This is the "leverage effect" that is prevalent in equity index returns (Bollerslev, 2007). Further, the EGARCH model is appealing because it does not require any parameter restrictions to ensure that the conditional variance of the returns is always positive (Campbell *et al.*, 1997).

The second GARCH-type specification, the GJR-GARCH in 3.5 is due to Glosten *et al*. (1993).

$$
\begin{aligned}
&r_t = \mu_t + \eta_t, \\
(3.5)\quad &\eta_t \mid (\eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t), \\
&h_t = \omega + f_1\left(\eta_{t-1}^2\right) + f_2 h_{t-1} + \kappa S_{t-1}\left(\eta_{t-1}^2\right),
\end{aligned}
$$

Where, $S_{t-1} = \begin{cases} 1 \; if \; \eta_{t-1} < 0 \\ 0 \, otherwise \end{cases}$

The volatility parameter κ captures the asymmetric effect in the GJR-GARCH model and it depends on the values of the dummy S. When $\kappa > 0$, the negative shock has a larger impact on the conditional volatility than does the positive shock. We can as well say that if the "leverage effect" exists, then $\kappa > 0$.

To examine the dynamic contribution of self-attribution bias to investor overconfidence, we follow Chuang and Lee (2006) specification of the following regression model,

$$
(3.6)\quad v_{xt} = \alpha_0 + \alpha_1 r_t + \sum_{j=1}^{p} \beta_j (r_{t-j} \times I_{t-j}) + \sum_{j=1}^{p} \gamma_j (r_{t-j} \times (1 - I_{t-j})) + \sum_{j=1}^{p} \lambda_j \left|\eta_{t-j}\right| + \varepsilon_t,
$$

where v_{xt} [18]is the detrended trading volume, η_t is the forecast error or the unexpected return derived from the GARCH specifications, $|\eta_t|$ is the absolute value of η_t and I_t is a dummy variable that takes on the value of one if $\mu_{t-1} \times r_t > 0$ in which μ_t is the expected returns derived from the GARCH specifications and zero otherwise. The impact of self-attribution bias on trading volume in the market is captured by two coefficients- β_j and γ_j. Specifically, β_j coefficient measures the effect of investor overconfidence on trading volume when they (investors) make right forecasts whereas γ_j coefficient measures the effect of investor overconfidence when they make wrong forecasts. To capture the impact of the precision of investors' forecasts on their level of overconfidence, we examine the behaviour of the coefficient λ_j.

Self-attribution bias predicts that investors tend to trade more actively following market gains as their forecasts turn out right than as their forecasts turn out wrong. Evidence of investors' self-attribution bias leads to positive values of the coefficients β_j and γ_j, and $\sum_{j=1}^{p}\beta_j > \sum_{j=1}^{p}\gamma_j$. Besides, we expect the increased precision of investors' forecasts to increase their overconfidence level. This is so because the relation between trading volume and the past absolute value of forecasts is used to show the quality or precision of forecasts;

[18] The subscript x indicates that two such regressions are estimated each at a time incorporating investors' forecasts from the EGARCH and the GJR-GARCH. Hence, we estimate four regression equations for the two types of trading volume measures.

a negative value of λ_j would imply that investors overconfidence increases with the precision of their forecasts and they therefore engage in more trading.

3.2.3 Overconfidence and volatility

Investors' overconfidence behaviour is a source of increased volatility in the market (Odean, 1998b). It is against this background that Chuang and Lee (2006) suggest a decomposition of trading volume into two components that include volume related to overconfidence and one that is not. In doing so, one is able to test which form of volume contributes to overconfidence the most.

The hypothesis that we test is whether excessive trading of overconfident investors in securities contributes to excess volatility.[19] The empirical framework employed to identify whether the observed excessive volatility is due to investor overconfidence, is attributed to Chuang and Lee (2006) whose regression formulation decomposes trading volume into two components.

$$(3.7) \qquad v_t = \alpha + \sum_{j=1}^{p} \beta_j r_{t-j} + \varepsilon_t = \left(\sum_{j=1}^{p} \beta_j r_{t-j} \right) + \left(\alpha + \varepsilon_t \right) = OVER_t + NONOVER_t .$$

In equation 3.7, the sum of the constant and residual terms is the component of trading volume unrelated to investors' overconfidence ($NONOVER_t$). The difference between

---

[19] The above hypothesis does not necessarily mean that excessive trading of overconfident investors is the sole source of excessive volatility.

trading volume and the sum of the constant and residual terms is the component of trading volume related to investors' overconfidence due to past stock returns ($OVER_t$). The importance of the two components of trading volume is to enable us augment the conditional variance equations of the symmetric GARCH (1, 1) and the asymmetric EGARCH models in order to examine if overconfidence-related trading increases volatility.

$$\begin{aligned}
&r_t = \mu_t + \eta_t, \\
(3.8)\quad &\eta_t \mid (v_t, \eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t), \\
&h_t = \omega + f_1(\eta_{t-1}^2) + f_2 h_{t-1} + f_3 NONOVER + f_4 OVER_t,
\end{aligned}$$

and

$$\begin{aligned}
&r_t = \mu_t + \eta_t, \\
(3.9)\quad &\eta_t \mid (v_t, \eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t), \\
&\ln h_t = \omega + f_1\left(\frac{|\eta_{t-1}| + \kappa\eta_{t-1}}{\sqrt{h_{t-1}}}\right) + f_2 \ln h_{t-1} + f_3 NONOVER_t + f_4 OVER_t,
\end{aligned}$$

where μ_t is the mean of market returns r_t conditional on past information. It is through combining equations 3.7, 3.8, and 3.9 that we are able to distinguish between excessive trading of overconfident investors from other factors that affect market volatility. The parameter f_4 captures the overconfidence effect on volatility whereas f_3 depicts other possible explanations for excessive volatility.

We anticipate that if there is excessive trading by overconfident investors in the securities market, then the occurrence of excess volatility is inevitable. Hence, from the model in expression 3.8 and 3.9, if overconfidence-based volume contributes to the conditional volatility then one expects to have $f_4 > f_3 > 0$.

3.2.4 Data type and sources

We construct weekly observations from the daily price lists published by the NSE for the period from 2 January 2001 to 31 August 2010 yielding five hundred and two (502) trading weeks. Our sample constitutes the NSE-20 share constituent stocks that have made the index for not less than five consecutive years hence nine securities are considered[20]. Further, for a security to be included, its record of shares traded, shares outstanding and share price must be available. The nine securities satisfying the above criteria include the following- Kenya Airways, Nation Media Group, Barclays Bank of Kenya, Kenya Commercial Bank, Standard Chartered Bank, Bamburi Cement, British American Tobacco, East African Breweries, and Kenya Power and Lighting Company. We compute the market returns (or the market-wide returns) from the NSE-20 share index, which is a price-weighted index. It is constructed as a weekly natural logarithm of Thursday's closing value to the next Thursday's closing value. This choice is dictated by the fact that empirical studies on the NSE indicate predictable returns on Fridays and Mondays unlike other trading days in the week, (Onyuma, 2009) hence the need to minimise biased patterns in the market returns.

[20] Between 2003 and 2010, the NSE-20 share index was revised five times, leading to the inclusion and exclusion of a number of stocks (NSE, 2010). For consistence purposes, we consider only those stocks that have made the index for no less than five years.

Further, we employ turnover defined as number of shares traded to the number of shares outstanding to proxy trading volume. The weekly trading turnover is computed as a summation of Friday's trading turnover to the following Thursday's turnover. The time aggregation method of summing turnover across dates suffices because summed turnover is cumulative and linear, each component of the sum corresponds to the actual measure of that trading day and is unaffected by neutral changes of units such as stock splits and share dividends, (Lo and Wang 2000). Further, we create equal-weighted and value-weighted turnover using the nine (9) stocks of the NSE-20 share index in order to conduct the analysis. Since trading volume data are decidedly non-normal, their natural logarithm transformations are preferred in empirical applications because they offer a symmetric distribution that stands out well to standard normality tests (Richardson *et al*., 1986; Ajinkya and Jain, 1989).

3.2.5 Returns, turnover series and detrending

3.2.5.1 The Returns Series

Campbell *et al*. (1997) argue the case for preference of stock returns to stock prices in both theoretical and empirical financial economics studies. The benefit of using returns in empirical works comes from their possession of attractive statistical properties such as stationarity and ergodicity, which is not the case for prices (Tsay, 2005).

To construct the market returns R_t one uses the daily NSE-20 share index to derive the expression in 3.10.

(3.10) $R_t = \left(\frac{I_t - I_{t-1}}{I_{t-1}}\right)$[21],

where I_t (the closing value of the index in the current week)and I_{t-1} (the closing value of the index in the previous week). For ease of modelling of the statistical behaviour of asset and market returns over time, we convert equation 3.10 into continuously compounded returns or log returns through the processes outlined in equations 3.11 and 3.12.

(3.11) $R_t = \frac{I_t}{I_{t-1}} - 1,$

Equation 3.11 implies that the simple gross return on the market index is just one plus the net return, $1 + R_t$ and it therefore follows that equation 3.12 holds.

(3.12) $r_t \equiv \log(1 + R_t) = \log\left(\frac{I_t}{I_{t-1}}\right) = l_t - l_{t-1},$

where $l_t \equiv \log I_t$. In the spirit of Campbell *et al*. (1997), we conclusively represent the market index (NSE-20 share index) as a natural logarithm of its gross return $(1 + R_t)$ denoted r_t.

[21] The inclusion or exclusion of dividends in the calculation of stock returns in studies involving trading volume and market returns does not alter conclusions (Gallant *et.al.*, 1992 and Hiemstra and Jones, 1994).

3.2.5.2 Turnover series

The ratio of the number of shares traded to the number of shares outstanding yields the turnover or relative volume. This is the trading volume measure employed in the majority of studies (see Campbell *et al.*, 1993; Lo and Wang, 2000; Llorente *et al.*, 2002; Chuang and Lee, 2006; Statman *et al.*, 2006). The measure of trading volume is given by the turnover T_{jt} of a given stock j at time (week) t as expressed in equation 3.13.

$$(3.13) \quad T_{jt} \equiv \frac{X_{jt}}{N_j},$$

where X_{jt} is the share volume of security j at time (week) t and N_j is the total number of shares outstanding of stock j. To take into account the size effect we employ both equal- and value-weighted volume series measures as expressed in equation 3.14.

$$(3.14) \quad T_t^{VW} \equiv \sum_{j=1}^{J} \omega_{jt}^{VW} T_{jt} \quad \textit{and} \quad T_t^{EW} \equiv \frac{1}{J}\sum_{j=1}^{J} T_{jt},$$

where $\omega_{jt}^{VW} \equiv \frac{N_j P_{jt}}{\sum_j N_j P_{jt}}$, *for* $j = 1,..., J$ *and* P_{jt} *is price of stock j at time t*. The term ω_{jt}^{VW} yields the weight of stock j at time t in establishing the value-weighted turnover T_t^{VW} whereas T_t^{EW} depicts the equal-weighted turnover. The turnover we employ in this study is in two forms- (i) weekly equal-weighted turnover, and (ii) weekly value-weighted turnover; all these are log transformed that is, $v_t^{ew} = \log T_t^{EW}$ and $v_t^{vw} = \log T_t^{VW}$.

3.2.5.3 Detrending

Whereas the returns series are by definition stationary in levels, the trading volume series are not. Enormous empirical studies that involve several trading volume proxies such as aggregate turnover, individual turnover, total number of trades or trade counts among others exhibit non-stationarity (see Campbell *et al*., 1993; Lo and Wang, 2000; Llorente *et al*., 2002; Ngugi, 2003b; Statman, *et al*., 2006; Chuang and Lee, 2006). It is against this background that several detrending[22] methods are put forth to deal with the trend in turnover series so as to achieve stationarity since the statistical theory underlying time series analysis requires stationarity of the underlying series. Much as there are weaker and stronger definitions of stationarity, it is sufficient especially in financial time series analysis to utilise the former otherwise known as covariance stationarity due to the difficulties involved in the empirical verification of the latter (Tsay, 2005).

An appropriate representation of the non-stationarity in economic and financial time series is important for one is able to avoid spurious detrending techniques that might render inference meaningless (Nelson and Ploser, 1982). Detrending of a trending time series aims at removing the trend in order to have a detrended series that is covariance stationary. The method of detrending depends on the form of the available trend: deterministic or stochastic for inappropriate trend elimination procedures generate artificial movements in resulting time series (Kirchgassner and Wolters, 2007).

[22] Raffalovich (1994) argues that techniques for removing trends from time series must be dictated by the processes that produced those trends. Appropriate detrending procedures depend on the correct identification of the sources of non-stationarity.

In the spirit of Cheung and Chinn (1996), we investigate the unit root property of the NSE turnover series in their different definitional forms to ascertain if they are trend or difference-stationary. In this regard, we employ the Augmented Dickey Fuller (ADF) test, which has the unit root process as the null hypothesis and trend-stationary as the alternative. Further, we subject the turnover series to the Kwiatkowski, Phillips, Schmidt and Shin (1992, hereafter KPSS) unit root test that has trend-stationarity as the null and the unit root process as the alternative. The idea is to have the two tests to corroborate each other's results in order to enable us decide upon the appropriate detrending method.

The concurrent use of the ADF with the KPSS tests is dictated by the inherent weaknesses of the former. Specifically, the ADF has a lower power when it comes to detecting the difference between the unit root and near random walks especially when the sample size is small (Shi *et al.*, 2012). The advantage of the KPSS is that to some extent it helps in solving the inadequacies of the ADF test. The KPSS test can distinguish series that appear to be stationary, series that appear to have unit roots and those for which the data are not sufficiently informative to be sure whether they are stationery or integrated.

In order for one to discriminate between a difference-stationary process (stochastic trend process) and a trend-stationary process (deterministic trend process) we adopt Cheung and Chinn's (1996) illustrative framework tabulated in Figure 3.1. Cell 1 represents a scenario in which both the ADF and KPSS tests fail to reject their respective null hypothesis, whereas cell 2 shows a scenario in which the ADF fails to reject the unit root null while the KPSS rejects the trend stationary null in favour of the unit root hypothesis. Cell 3 depicts a scenario in which the ADF rejects the unit root null in favour of the stationary alternative and the KPSS test accepts the trend stationary null while cell 4 depicts the case in which both the ADF and KPSS reject their respective null hypotheses.

Figure 3.1: Unit root and trend stationary analytical framework

	KPSS (fail to reject)	KPSS (reject)
ADF((fail to reject)	*Cell 1*	*Cell 2*
ADF (reject)	*Cell 3*	*Cell 4*

Source: Cheung and Chinn (1996)

A series that falls in cell 2 shows a strong evidence of presence of unit root in the data while one that falls in cell 3 shows a strong evidence of trend stationarity. On the one hand, series falling in cell 1 may be due to the low power of both ADF and KPSS tests that makes it difficult to reject neither of the null. Put differently, the data may not contain sufficient information to enable one discriminate between the trend stationary and difference stationary hypotheses. On the other hand, cell 4's representation of a rejection of the two hypotheses by the two tests signals a complex data generating process than the standard trend and difference stationary classification. Besides, the presence of nonlinear trends and or structural breaks can be a source of such a result.

We take care of Perron's (1989) argument that evidence of the presence of unit roots rests on failure to account for structural changes in the underlying data generating process by employing the Zivot and Andrews (1992) test. Perron (1989) proposes that one needs to incorporate an exogenous structural break whose date is assumed known *apriori* in the unit root tests. Banerjee *et al*. (1992), Christiano (1992) and Zivot and Andrews (1992) show that endogenising the structural break date minimises the bias of over rejecting the unit root null hypothesis. Hence, we employ the Zivot and Andrews (1992) test that uses a data-dependent algorithm to proxy break points in unit root analysis.

Ngugi (2003b) finds the trading volume data of the NSE to exhibit both linear and non-linear time trends consequently turnover data is regressed on a deterministic function of time as depicted in equation (3.15). This study employs this type of detrending in order to achieve stationarity of the turnover series.

(3.15) $v_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t$,

where $v_t = v_t^{ew}$ *and* v_t^{vw} that is the natural logarithms of equal-weighted and value weighted turnover respectively.

3.3 The Econometric models for index revisions

To test index revisions relating to the NSE-20 share index the study employs the event study methodology[23]. Following Brown and Warner (1980, 1985) and MacKinlay (1997), one can

[23] This study only concentrates on examining individual security returns and market returns in order to capture the price effects and leaves out volume effects because of data irregularities in the market's trading volume.

use financial market data to measure the impact of a specific event on a firm's value through an event study. In what follows, we lay out this procedure in relation to testing the index effects using the NSE data.

3.3.1 Defining the event of interest

In this study, the event of interest is the entry or deletion of a given stock from the NSE-20 share index. In some studies the announcement of an entry or exit is the event whereas in others it is the actual entry or exit that is defined as the event. This study defines the event as the actual revision and not the announcement of a revision because of two reasons. First, there is a variation in the number of days preceding the revision of the index. In other words, the NSE appears to have no policy regarding the number of days it takes to effect a revision in the index (see Table 3.1). Second, treating each revision in isolation from each other is unlikely to give meaningful results because one needs to aggregate across securities and through time to obtain the market's cumulative abnormal returns.

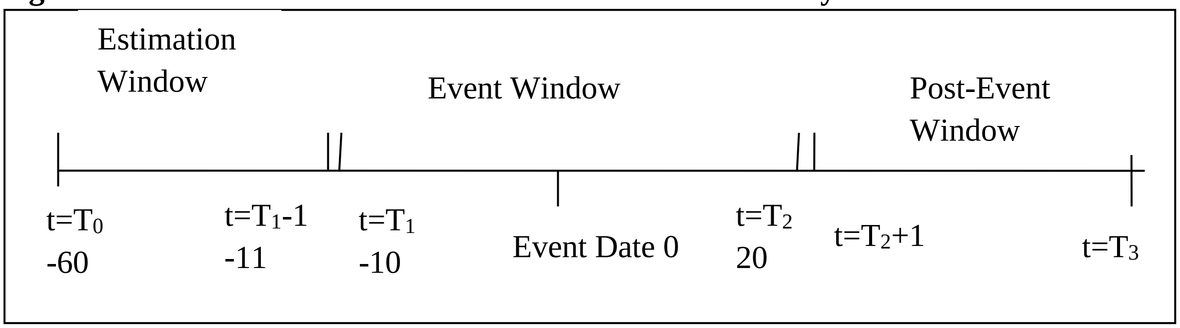
Having defined the event of interest, one needs to identify the period over which the security prices of the firms involved in the event will be examined- the event window. MacKinlay (1997) argues that it is customary to define the event window to be larger than the specific period of interest as it permits examination of periods surrounding the event.

Prior studies indicate a variation in the length of the event window depending on the characteristics of the market under review. Shleifer (1986) uses a symmetric pre-event and post-event window that comprises 20 days before and 20 days after the event (-20, 20) whereas in Harris and Gurel (1986) it is defined as 10 days before and 30 days after the event (-10, 30). Dhillon and Johnson (1991) define their event window over the period starting 10 days before and ending 20 days after the event. Li and Sadeghi (2009) decompose the event window over both a longer horizon of (-30, 45) days and compare the results with shorter time horizons of (-5, 5), (-10, 10) and (-20, 20) to ensure the robustness of the estimates. Obere (2009) uses a window of 20 days before and after the event (-20, 20) in studying the impact of dividend announcements on the value of the NSE-listed firms[24].

This study employs an event window of 31 days that is (-10, 20) to observe the changes in securities' returns that are affected by the index revision. This partly follows from MacKinlay (1997)'s argument that an economic event's impact on a security are easily traceable in a security's prices observed over a relatively shorter time period. Additionally, the event studies literature offers no rule of thumb on the length of neither the event window nor the estimation window, but rather suggests that the specific market characteristics such as the available data dictate these choices. Therefore our estimation window consisted of 50 trading days whereas the event window consisted of 31 trading days; all these refer to event-time trading days and not calendar days. Figure 3.2 gives a visual timeline of the study's event in which the 50-day length (L) estimation window is given by $L_1 = T_1 - 1 - T_0$ and that of the 31-day event window is given by $L_2 = T_2 - T_1$.

[24] In choosing the event window of (-20, 20), Obere (2009) argues that such a time horizon is long enough to provide adequate data for measuring returns and facilitating regression analysis and not too large to cause event overlap.

Figure 3.2: The framework of the timelines of the event study



Source: Author's formulation based on MacKinlay *et al*, (1997)

3.3.2 Selection criteria of securities considered in the study sample

The period we consider in this study is between May 19, 2003 and November 5, 2010 in which five index revisions took place and resulted in 13 deletions from and 13 inclusions into the NSE-20 share index as depicted in Table 3.1.

Table 3.1: Exclusions and Inclusions at the NSE for 2003-2010

Firms excluded	Firms include	Announcement Date	Change Date

1	E.A Packaging Ltd	NIC Bank Ltd	Missing	May19,03
2	Unilever Tea Kenya Ltd	Mumias Sugar	Jul20,07	Aug01,07
3	Williamson Tea Kenya	Express Ltd	Jul20,07	Aug01,07
4	Kakuzi	Rea Vipingo	Jul20,07	Aug01,07
5	Uchumi	CMC Holdings Ltd	Jul20,07	Aug01,07
6	B.O.C Kenya Ltd	KenGen Ltd	Jul20,07	Aug01,07
7	NIC Bank Ltd	I.C.D.C Investments	Jul20,07	Aug01,07
8	TPS Eastern Africa Ltd	Safaricom Ltd.	June26,08	July01,08
9	Diamond Trust Bank	Equity Bank Ltd	June26,08	July01,08
10	Total Kenya Ltd	Athi River Mining	June26,08	July01,08
11	Sameer Africa Ltd.	E.A.Cables Ltd	June26,08	July01,08
12	Centum Investment Co.	Co-operative Bank	Nov30,09	Dec01,09
13	E.A.Cables Ltd	KenolKobil Ltd.	Sept30,10	Oct01,10

Source: NSE (2010) and NSE data base

This study employs three key criteria to guide the choice the number of firms to consider in the analysis. First, any firm considered for inclusion into or exclusion from the NSE-20 share index was never involved in any form of merger or acquisition event; second, there were no stock split and dividend payment announcements for the firms in the sample at least during the event window; and three the firms had adequate data points to be used in the event time period. The first two criteria ensure that no other event could have affected the returns of the firms considered whereas the last one ensures that the data set satisfies statistical requirements for regression analysis.

Of the 13 securities that were added to the market index, only Safaricom Limited failed to beat the selection criteria because it lacked sufficient data points. This is due to the fact that Safaricom was officially listed at the exchange on June 9, 2008 and subsequently added to the market index on July1, 2008[25] hence it could not generate sufficient data for the estimation period. Therefore, this study considers only 12 securities as the only ones added to the NSE-20 share index.

Similarly, not all the 13 securities deleted from the market index make it into this study's analysis. East African Packaging limited applied for voluntary delisting after Canadian Overseas Packaging Industries took over its ownership in 2003; BOC limited was involved in a merger with a listed company called Carbacid on December5, 2005 which led to a suspension of the trading of its shares up to November 2009. Uchumi Supermarket had no data subsequent to the deletion date for the NSE had suspended the trading of its shares on June 1, 2006 due to the firm's insolvency[26]. Further, we dropped NIC limited because it announced a bonus issue as well as a rights issue on July 26, 2007. Unilever Tea, Williamson Tea and Kakuzi which lie in the agricultural segment are dropped due to too much infrequent trading[27]. Consequently the analysis on deletion of securities from the NSE-20 share index utilizes the following 6 securities: TPS Eastern Africa Limited, Diamond Trust Bank, Total Kenya Limited, Sameer Africa Limited, Centum Investment Company and East African Cables Limited.

[25] Much as the regulations governing the NSE-20 share index require a company to have been trading at the exchange for a minimum of one year prior to inclusion, the NSE Board waived this requirement because safaricom Limited had had a significant impact on the market capitalisation and trading activity within a short time period.
[26] However on May 31, 2012 the company was officially re-listed.
[27] This means that these securities fail to trade for 4 consecutive days in a week.

3.3.3 Choice of the normal performance model and the estimation window.

To be able to appraise the impact of inclusions into and exclusions from the NSE-20 share index one needs a measure of abnormal returns vis-à-vis the normal returns. MacKinlay (1997) defines abnormal returns as the actual *ex post* return of the security over the event window minus the normal return of the firm over the event window. Brown and Warner (1980, 1985) argue that the occurrence of abnormal returns signify the presence of a given benchmark. Normal returns constitute that particular benchmark; hence they are defined as the expected returns if there are no events. The normal returns therefore, are estimated over a period of time outside the event window. There are basically two broad approaches applied in estimating normal returns- statistical and economic models[28].

We employ a statistical model- the market model as shown in equation 3.16- in order to capture the normal returns of the NSE.

(3.16) $r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \quad E(\varepsilon_{it}) = 0 \ and \quad Var(\varepsilon_{it}) = \sigma^2_{\varepsilon_t}$

Equation 3.16 is the market model and it relates the period-t returns (r_{it}) on a given security to the return of the market portfolio (r_{mt}). ε_{it} is the zero mean disturbance term whereas α_i and β_i are the market model parameters and $\sigma^2_{\varepsilon_t}$ is the variance of the disturbance term. The study employs the NSE-20 share index as the proxy for the market portfolio.

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[28] Statistical models dominate economic models in empirical works because they have an advantage of eliminating unnecessary biases inherent in economic models (MacKinlay, 1997). Thus, this study adopts the statistical models in measuring normal performance.

The infrequent trading of securities in frontier and emerging markets leads to biased beta estimates (systematic risk of a share) in the market model. According to Dimson (1979), the major source of bias is the tendency for prices recorded at the end of a time period to represent the outcome of a transaction that occurred earlier in or prior to the period in question. This is a likely possibility in the case of the NSE where the market prices of securities indicate non-changing prices over a given time period which yields consecutive zero returns. Similarly, shares that suffer from non-trading also have their covariance with the market substantially underestimated. The immediate outcome of these biases is that infrequently traded securities have beta estimates that are biased downwards whereas for frequently traded securities their beta estimates will be upward biased.

The most popular methods dealing with infrequent trading/thin trading problems are Scholes and Williams' (1977) approach and Dimson's (1979) aggregated coefficients approach. In addition to these, there are three other approaches namely- the adjusted simple regressions; simple regressions with overlapping observations and trade-to-trade regressions. The Dimson method derives its popularity from the fact that it neither requires the market index to be continuously traded nor supplementary data such as transaction information (Dimson, 1979; Strugnell *et al*., 2011, Bundoo, 2011).

In reality, what the Dimson method seeks to achieve is to ascertain the true systematic risk in equation 3.16 or the market model using security price data that is prone to infrequent trading. According to Dimson (1979), all that need be done is to run a multiple regression shown in equation 3.17 of security returns against lagged, matching and leading market terms. Consequently, a consistent estimate of beta is obtained by aggregating the slope coefficients from equation 3.17.

$$(3.17)\quad r_{i,t} = \alpha_i + \sum_{k=-p}^{p} \beta_{i,k} r_{m,t+k} + \varepsilon_{i,t}$$

The coefficients $r_{i,t}$ and $r_{m,t}$ represent the security and market returns in time period t respectively. The number of lead and lag terms p is variable and should be related to the degree of thin/non-trading in the market (Strugnell, *et al*., 2011). While the degree of thinness varies across markets, in empirical studies it's proxied by examining the consecutive zero returns in the data (Diacogiannis and Makri, 2008). Additionally, Dimson (1979) emphasizes that one should consider having more lags than leads for the former are more important than the latter in correcting for thin trading[29]. The Dimson market model beta coefficient for security i is then given by expression 3.18.

$$(3.18)\quad \beta_{i,t} = \sum_{k=-p}^{p} \beta_{i,k}$$

Equation 3.18 gives the value of the true beta as the sum of all the estimated betas in 3.17. It is this summation that gives the Dimson method an upper hand over the rest in dealing

[29] We chose 3 lags and 1 lead for the included stocks because the data set has between 2 to 4 consecutive zeros where as we chose 4 lags and 1 lead for the deleted stocks because the data set has 8 to 3 consecutive zeros.

with thin trading problems. In fact, Bundoo (2011) argues that in the presence of infrequent trading, an introduction of sufficient lags and leads to the market model eliminates all the non-trading bias thereby making the Dimson method to be more efficient than the Scholes-Williams method. Vazakides (2006) gives a simple intuition of the Dimson method as one that depicts the return on a specific security depends on past, present and future returns on the market portfolio.

3.3.4 Calculating and analysing the abnormal returns

In order for one to establish the impact of the event of index revisions of the NSE-20 share index, one needs to establish whether there are any abnormal returns that arise. Using the estimates of the simple market model (equation 3.16) and the Dimson aggregating coefficients method (equation 3.17), we are able to estimate the abnormal returns of each security over a chosen time horizon by applying the following relationships,

(3.19) $ar_{i,t} = r_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i r_{m,t})$

(3.20) $ar_{i,t} = r_{i,t} - (\hat{\alpha}_i + \sum_{k=-p}^{p} \hat{\beta}_{i,k} r_{m,t+k})$

In order for one to draw overall inferences about the inclusion and exclusion events, MacKinlay (1997) suggests that one needs to aggregate the abnormal return observations. The abnormal return observations must be aggregated for the event window and across observations. The individual securities' abnormal returns ($ar_{i,t}$) are aggregated over the sample to yield the average abnormal return (aar_t) for each day in the event window using the formula in equation 3.21.

(3.21) $aar_t = \frac{1}{n}\sum ar_{i,t}, \quad \text{where } n \text{ is the number of securities.}$

Over an interval of for example two or more trading days within the event window, one makes use of the cumulative average abnormal return $caar_{T_1,T_2}$ commencing at period $t=T_1$ to period $t=T_2$. The purpose of the cumulative average abnormal returns is to ascertain the performance of the securities over a multi-period interval (during the event time) since it sums over each day's average abnormal performance. For any interval in the event window we use the following expression in (3.22) to calculate the cumulative average abnormal returns.

(3.22) $caar_{T_1,T_2} = \sum_{t=T_1}^{T_2} aar_t$

3.3.5 Hypothesis testing

The study's objective is to establish the effect of index revisions of the NSE-20 share index on the value of the affected stocks. The null hypothesis we then test is that the index revision event yields zero abnormal returns in the affected securities. In effect, it is the statistical significance of the cumulative average abnormal returns in equation 3.22 that are tested using an appropriate test statistic. Hence for the $caar_{T_1,T_2}$ given in equation 3.22, a standard test statistic is the $caar_{T_1,T_2}$ divided by an estimate of its standard deviation as expressed in equation 3.23.

$$(3.23) \quad t - test = \frac{caar_{T_1,T_2}}{\mathrm{var}(caar_{T_1,T_2})^{1/2}} \sim \mathrm{N}(0,1)$$

To ascertain the variance term in 3.23 we use the residual variance as its proxy that is calculated within the estimation period as is represented in expressions 3.24 and 3.25.

$$(3.24) \quad \hat{\varepsilon}_{i,t} = r_{i,t} - \hat{r}_{i,t} = r_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i r_{m,t}); \quad for \ t = T_0, \ldots\ldots, T_1 - 1$$

$$(3.25) \quad \sigma_{\varepsilon}^2 = \frac{1}{N - \Omega} \sum_{t=T_0}^{T_1-1} \hat{\varepsilon}_{i,t}^2 ,$$

where Ω is the number of parameters in the regression in the estimation period and N is the number of observations.

3.4.6 Summary of estimation technique for index effects

In summary, the event study procedure is applied in estimating index effects. The event date is defined as the one when the revision takes place. For each event we divide the time series data into the estimation and event window for the purposes of measuring the benchmark parameters and the abnormal returns respectively. We employ both the market model and the Dimson market model when estimating the bench mark parameters in the estimation window to ensure robustness of the results. The resulting abnormal returns in the event window show the effect of the event on the value of the affected securities. However, inference on whether the event has a significant impact or not is made using the cumulative average abnormal returns generated from aggregating over the average abnormal returns of the event window.

CHAPTER FOUR

FINDINGS AND DISCUSSION

4.1 Introduction

This chapter aims at presenting and discussing the study's findings on the overconfidence bias and index revision objectives. The overconfidence bias results are structured as follows- we start by presenting the summary statistics and other time series properties of the data which is followed by the static and biased-self attribution bias along with some diagnostic tests. The results on overconfidence and return volatility complete the presentation of the first objective. The index revision results based on the graphical formulations and tabulated cumulative average abnormal returns[30] conclude this chapter.

4.2 Findings pertaining to the overconfidence bias

4.2.1 An overview of the summary statistics

Table 4.1 captures two issues- the descriptive statistics and the first 10 autocorrelations of the study's variables. The descriptive statistics suggest that the equal-weighted turnover series has a weekly mean of 0.16% whereas that for the value-weighted one is 0.07% and the standard deviations for the two volume indices is 0.11% and 0.05% respectively. The variation of these two around their means is slightly higher in the equal-weighted turnover whose coefficient of variation is 69.4% as compared with that of the value-weighted turnover

[30] We conduct stationarity tests on the market and individual returns variables used in the market and Dimson models used in generating the cumulative average abnormal returns though we do not report these results. The results indicate that returns are stationary in levels just as expected due to their definition.

of 67.7%. Overall, there is a high variation in both proxies of weekly trading volume of the NSE over the period 2001 to 2010.

Table 4.1: Summary Statistics of the variables used in Overconfidence Analysis

Variable	log market return	log equal-weighted turnover	log value-weighted turnover
Mean	0.173	0.161	0.077
Median	0.171	0.133	0.068
Maximum	23.67	0.801	0.468
Minimum	-11.46	0.008	0.006
Standard Deviation	3.136	0.112	0.052
Coefficient of Variation	18.07	0.694	0.677
Skewness	1.011	1.567	1.656
Kurtosis	11.228	6.797	9.276
Jarque- Bera Statistic (p-value)	1501 (0.000)	507.2 (0.000)	1053 (0.000)
Observations	502	502	502
Autocorrelations			
ρ_1	0.063	0.563	0.570
ρ_2	0.047	0.441	0.461
ρ_3	0.087	0.371	0.401
ρ_4	-0.058	0.425	0.413
ρ_5	0.015	0.376	0.391
ρ_6	0.131	0.351	0.410
ρ_7	0.000	0.306	0.402
ρ_8	0.015	0.313	0.428
ρ_9	0.048	0.291	0.366
ρ_{10}	-0.023	0.284	0.358
Box- Pierce Q(10) (p-value)	19.02 (0.039)	737.28 (0.000)	914.84 (0.000)

Source: Author's own calculations.

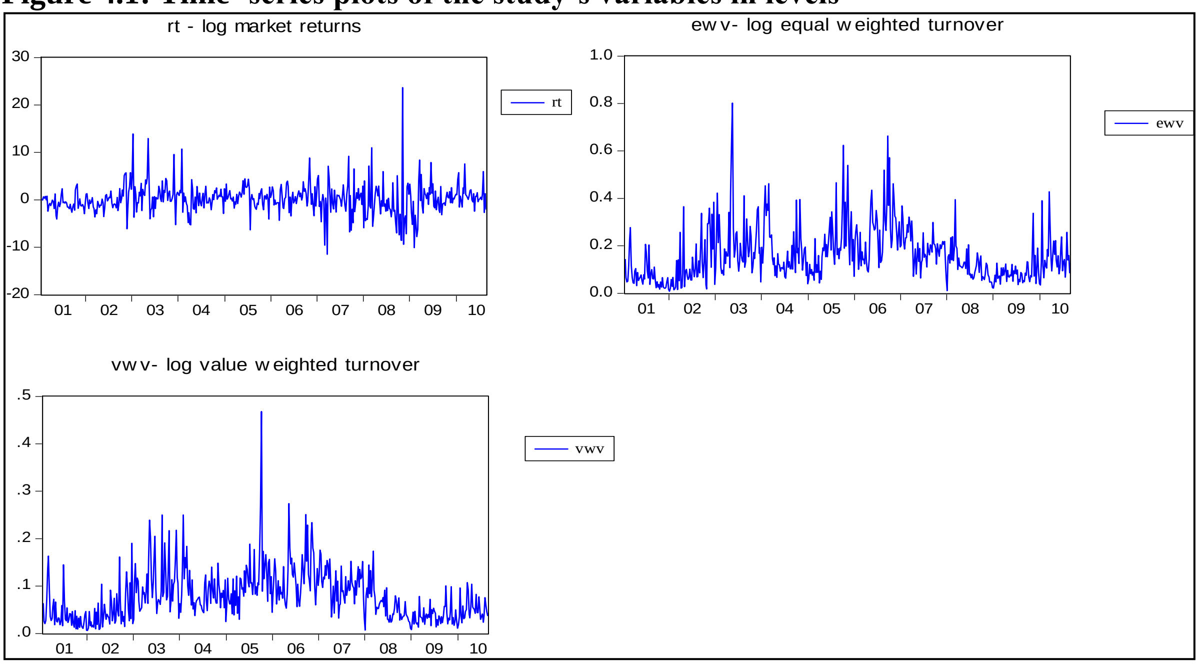
The weekly mean returns series is 0.17% with a corresponding standard deviation of 3.14%, which is an indication of high volatility in the market returns. The weekly coefficient of variation of the returns stands at 1,807%, which is a pointer to a high variability in the weekly returns over the study period. We can also conclude from these descriptive statistics that there is a higher variability in the weekly returns as compared with the weekly turnover.

The positive skewness of all the study's variables implies presence of asymmetries in the distributions, specifically the occurrence of long right tails. In addition, the distributions of the series are leptokurtic (peaked) relative to the normal ones as evidenced by their kurtosis values that exceed three (3). This specifically means that all the variables in this study have higher peaks around their mean values. Essentially, skewness indicates non-normality while the relatively large kurtosis is indicative of the fact that the distributions of both the returns and volume series are leptokurtic, which is a clear signal of peaked distributions.

We reject the null hypothesis of normal distribution of the series at all the conventional test sizes as evidenced by the Jarque-Bera Statistic and its corresponding probability values across all the variables. In addition, we examine non-normality by plotting quantile-quantile (Q-Q) plots of all the underlying variables. If the underlying distribution is normal then the Q-Q plot should lie on the 45 degrees straight line. If a series does not lie on this line, then it is non-normal. The Q-Q plots presented in Appendix Figure1.1 confirm the non-normality of the study's variables since the plots do not lie on a straight line.

The lower segment of Table 4.1 depicts the first 10 autocorrelations of the series and the corresponding Box-Pierce/Ljung-Box Q-Statistic. The purpose of displaying the autocorrelations is to figure out probable non-stationarities in the variables by examining the decaying process in the autocorrelations as lags increase. The weekly returns variable has the lowest autocorrelations that start at 0.063 and fall to 0.047 at lag 2, increasing to 0.084 at lag 3 and subsequently falling to 0.000 at lag 7. Such a pattern of decay in the autocorrelations is common in stationary time series. Besides, by definition, one would expect the weekly returns series to be stationary in levels. The two measures (proxies) of trading activity, that is the value-and equal- weighted series display slow decay that is characteristic of integrated time series. Figure 4.1 depicts the trends in all the variables. From Figure 4.1, it is clear that the turnover series display a strong time trend as suspected earlier whereas the returns seem to be relatively stationary.

Figure 4.1: Time- series plots of the study's variables in levels



For illustrating some stylised facts about the NSE weekly market-wide returns data, we examine the correlograms of the returns and its squared component (squared weekly market returns). To figure out unpredictability of market returns and volatility clustering features, one examines the autocorrelations and the Ljung-Box-Q statistics for 36 lags for the weekly returns and squared returns respectively[31].

Appendix Tables 1.4 and 1.5 show the correlograms of the weekly return series and its squared component. The weekly returns series depicts mixed results in terms of the presence of autocorrelation. Its first two lags are not significant where as its third and fourth lags are significant with the fifth lag not being significant. Lag 7 up to lag 26 depicts significant autocorrelations and this is evidence of higher order serial correlation in the weekly returns series. Its counterpart the squared returns series depicts a strong evidence of presence of serial correlation from lag 1 up to the last lag of 36.We reject the null hypothesis of no serial dependence in the returns and squared series of the NSE.

One can therefore argue that there is evidence of linear (weekly returns) and non-linear (squared weekly returns) dependency in the series. Of particular interest is to establish evidence of volatility clustering. The significant autocorrelation in the squared returns series is proof for the presence of volatility clustering. Lastly, a critical examination of the Ljung-Box-Q statistics of both the returns and squared returns series reveals that the value is higher in the latter case than in the former one. What this translates into is that non-linear time dependency is stronger than linear time dependency.

[31] The rationale for providing this information is to (i) provide evidence for the presence of autocorrelations in the returns and subsequently aid the proper specification of the mean equation when we estimate the ARCH/GARCH type of models; and (ii) show presence of volatility clustering that justifies use of GARCH models.

4.2.2 Unit root and Stationarity tests.

In the spirit of Cheung and Chinn (1996) we conduct unit root/ stationarity test to achieve mainly two objectives- (i) differentiating difference stationary processes from trend-stationary ones and (ii) achieving stationarity of data in case of the presence of nonstationarities. Since, the two volume proxies of equal-weighted turnover and value-weighted turnover exhibit some trend (see Figure 4.1), we conduct the tests using the 'intercept and trend' deterministic trend assumption. The appropriate lag length for the ADF test is selected using the Schwarz criterion whereas the KPSS is estimated using the Bartlett Kernel estimation method. We report the results in Table 4.2.

Table 4.2: Unit root vs trend stationarity

Variable	ADF in level	KPSS in level
Market returns r_t	-20.932	0.194
Equal-weighted turnover v_t^{ew}	-5.557	0.201
Value-weighted turnover v_t^{vw}	-5.666	0.205
Critical values	1% (-3.976)	1% (0.216)
	5% (-3.418)	5% (0.146)
	10% (-3.132)	10% (0.119)

Source: Author's calculations.

Comparing the ADF statistics of all the three variables to the 1% critical value, one is able to reject the null hypothesis of unit root. The KPSS test result for market returns rejects the trend-stationary null hypothesis at the 5% critical value whereas the equal-weighted and value-weighted turnover series fail to reject it at the 1% critical value. In the Cheung and Chinn (1996) framework of analysis, one can infer that the two measures of trading volume employed in this study are trend-stationary processes (stationary around a deterministic trend). The market returns series rejects the unit root and trend-stationary null hypotheses, a result that we expect in the former case and not in the latter one. One possible reason for such a contradiction might be the presence of structural breaks in the data we therefore subject all our variables to the Zivot -Andrews test whose null hypothesis is unit root process without any structural break.

Table 4.3: Zivot-Andrews one break test results in both intercept and trend

Variables	**lags**	**t-statistic**	**Break date**
Market returns r_t	3	-11.529	5-Feb-04
Equal-weighted turnover v_t^{ew}	3	-7.115	5-Apr-07
Value-weighted turnover v_t^{vw}	4	-7.614	5-Apr-07

Source: Author's Calculations

Note: (i) The critical values for Zivot-Andrews tests are -5.57 and -5.08 at 1% and 5% levels of significance respectively. Appendix Figures 1.2, 1.3 and 1.4 represent the graphs corresponding to the test above.

Table 4.3 reports the minimum t-statistics from testing the stationarity assuming a shift in mean and broken trend in the variables. The minimum t-statistic reported is the minimum overall break point in each regression of the Zivot-Andrews test from the first week to the last week of the study's variables. The Zivot-Andrews one-break results suggest that we can reject the unit root null for all the three variables at the 1% critical level. This result does not contradict the one obtained without considering structural breaks in Table 4.2.

Further, since turnover data are trend stationary as shown by the ADF and KPSS tests, we detrended them by running a regression of turnover on a deterministic function of time following Ngugi (2003b). Since the resulting residuals are the detrended turnover series we test for their stationarity and subsequently report the results in Table 4.4.

Table 4.4: Stationarity results for detrended turnover series

Variable	ADF	KPSS
Detrended equal- weighted turnover	-6.436	0.091
Detrended value-weighted turnover	-10.793	0.096
Critical values	1% (-3.443) 5% (-2.867) 10% (-2.569)	1% (0.216) 5% (0.146) 10% (0.119)

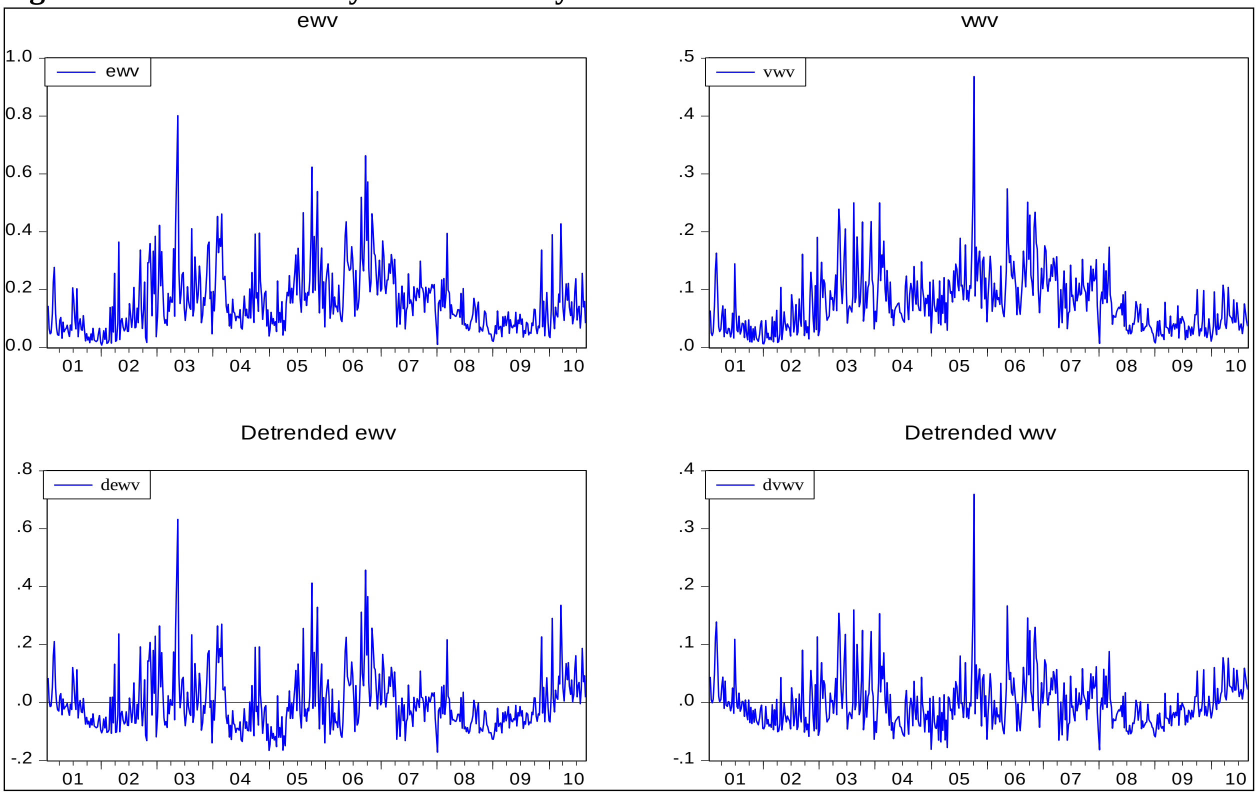
Source: Author's calculation.
Notes

(i) Results are based on the residuals of equation 3.15 ($v_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t$).

(ii) Since the trend in the equal and value-weighted turnover series has been dealt with, we now refer v_t^{ew} and v_t^{vw} as detrended equal and value-weighted turnover series respectively.

The ADF results that reject the unit root null hypothesis in the detrended series at all the conventional significance levels are corroborated by the KPSS results which fail to reject the null hypothesis of trend stationarity. In the spirit of Cheung and Chinn (1996) analysis, the turnover variables are trend stationary. A graphical view of the non-stationary equal and value weighted turnover series juxtaposed with the detrended series is depicted in Figure 4.2. It is evident from the figure that the detrended series achieve stationarity around a deterministic trend following detrending.

Figure 4.2: Non-stationary and stationary detrended turnover series



In summary, we achieve two things in this section. First, we are able to ascertain the kind of trend existing in the returns and turnover series so as to conduct appropriate detrending. The returns series are difference stationary (stationary around a stochastic trend) whereas the turnover series are trend-stationary (stationary around a deterministic trend). And secondly, the data depict no significant broken trends that would invalidate the stationarity and unit root tests conducted.

4.2.3 Static Overconfidence: Causality results

The seemingly unrelated regression (SUR) results from the estimation of equation 3.1 are reported in Appendix Tables 1.6 and 1.7. It is from these results that we are able to construct the Granger-causality test results, which we report in Table 4.5. The choice of the optimal lag follows an information criteria approach. Following the imposition of the restrictions implied by Granger-causality we report the following results in Table 4.5.

Table 4.5: Granger-causality Tests of Trading Volume and Market Returns

Dependent Variable	v_{1t}^{ew}		r_t		v_{2t}^{vw}		r_t	
Independent Variable	v_{1t-j}^{ew}	r_{t-j}	v_{1t-j}^{ew}	r_{t-j}	v_{2t-j}^{vw}	r_{t-j}	v_{2t-j}^{vw}	r_{t-j}
χ_1^2	140.795	26.095	3.430	11.214	86.0123	14.713	0.188	3.085
(p-value)	(0.000)*	(0.000)*	(0.488)	(0.024)**	(0.000)*	(0.001)*	(0.910)	(0.214)
Sum of lagged coefficients	0.618	0.008	0.173	0.146	0.443	0.003	-1.654	0.111
χ_2^2	125.931	11.432	0.007	2.624	80.087	11.279	0.185	3.021
(p- Value)	(0.000)*	(0.001)*	(0.931)	(0.1052)	(0.000)*	(0.001)*	(0.667)	(0.082)***
Q(5) (p-value)	0.538 (0.991)		0.169 (0.999)		3.810 (0.577)		6.581 (0.254)	

Source: Author's calculations based on regression results in Appendix Tables 1.6 and 1.7.

Notes:

(i) With the aid of seemingly unrelated regressions (SUR) technique, we estimated the causality relations between turnover and market returns of model 3.1 reproduced here below. The optimal lags are 4 and 2 respectively for equal-weighted and value-weighted turnover respectively.

$$v_t = \alpha_{11} + \sum_{j=1}^{p} \beta_{11j} v_{t-j} + \sum_{j=1}^{p} \beta_{12j} r_{t-j} + \varepsilon_{1t}$$

$$r_t = \alpha_{12} + \sum_{j=1}^{p} \beta_{21j} v_{t-j} + \sum_{j=1}^{p} \beta_{22j} r_{t-j} + \varepsilon_{2t}$$

(ii) The two χ^2 tests are based on joint causality restrictions that are imposed by the system. The first chi- square (χ_1^2) test statistic is estimated as a joint null hypothesis that incorporates the causality restrictions whereas the second one (χ_2^2) tests the null that the sum of the estimated coefficients is equal to zero. Also, *, ** and *** depict 1%, 5% and 10% significance levels respectively.

(iii) Q (5) depicts the Ljung-Box Q-statistic that tests the null hypothesis of no serial correlation in the residuals of each regression up to the specified lag of 5.We show the correlograms of each regression equation in the SUR system in the appendix section in Tables 1.8, 1.9, 1.10 and 1.11.

The null hypothesis ($H_0 : \beta_{12j} = 0$) that stock returns do not Granger-cause trading volume, is tested by imposing the restriction that $\beta_{12j} = 0$ for all j in both the equal and value-weighted turnover. The hypothesis that stock returns do not Granger-cause trading volume is rejected at all the conventional levels of significance for both the equal and value-weighted turnover. One draws such a conclusion by examining the chi-squared values (χ_1^2) of 26.095 and 14.713 for both the equal-weighted and value-weighted turnover series with corresponding $\rho - values$ of 0.000 and 0.001.A similar result is evident in Chuang and Lee (2006), Statman *et al*. (2006) and Glaser and Weber (2009). Intuitively, when investors earn higher positive returns in the current week, they do not expect this to change in the subsequent weeks. Consequently, they engage in more trade which raises the volume of trade at the NSE.

Further, we examine the sum of the lagged coefficients to ascertain the cumulative effect of lagged weekly stock returns on trading volume. This examination reveals that there is a positive and significant relationship between lagged stock returns and trading volume. Specifically, this relationship is significant at all the conventional levels in both equal and value-weighted turnover as evidenced in the chi-squared (χ_2^2) values of 11.432 and 11.279 with their corresponding $p - values$ of 0.001 and 0.001 respectively. The intuition of a significant and positive relation between returns and volume in the NSE is that the occurrence of market gains aids in predicting an increase in trading volume- a result that is consistent with the overconfidence hypothesis. In effect, investors at the NSE are likely to anticipate higher returns in the future weeks if they earn higher returns in the current week and subsequently engage in more trading.

Nevertheless, we need to put into consideration the fact that there are other trading volume theories that predict similar results like the overconfidence hypothesis does. For instance, Copeland (1976) and Jennings *et al*. (1981) suggest the presence of a positive bidirectional causal relationship between lagged volume and returns due to a sequential flow of information in the market. Further, De Long *et al*. (1990) propose that noise trader models can also predict a positive causal relation (feedback) in either direction. It is in this regard that we test the hypothesis that trading volume does not Granger-cause stock return (that is $\beta_{21j} = 0$ for all j). This hypothesis is equivalent to testing the existence of feedback in the model.

Our findings suggest that we are unable to reject the hypothesis that trading volume does not Granger-cause stock returns for both volume measures. The large $p-values$ of 0.488 and 0.910 that correspond to the chi-squared (χ_1^2) values of 3.430 and 0.188 for the equal and value- weighted turnover respectively serve as strong indicators of absence of a feedback relation between market returns and volume. Similarly, this result also suggests that the NSE is weak-form efficient since trading volume does not contain any information that can cause the market returns to change. In effect, this result stresses the fact that trading volume in the market cannot be used in the prediction of future market returns.

Besides, the relationship between the sum of lagged volume (turnover) and market returns is also statistically insignificant as seen from the χ_2^2 and the respective $p-values$ of 0.007 (0.931) and 0.185 (0.667). The absence of feedback also rules out the possible explanations from the sequential information flow and noise trader models that present similar results/predictions as the overconfidence hypothesis. Intuitively, an increase in volume does not lead to increased market returns (gains) for investors whereas in the presence of overconfident market players, increased market gains yield increased trading volume.

Further, we find a strong causal relationship between current volume and lagged volume in both equal-and value-weighted turnover. The cumulative effect of lagged volume on current volume is positive and significantly different from zero. Covrig and Ng (2004) present a similar result, but with a different methodology in which there is high autocorrelation between volumes traded, this is attributed to the correlated investment patterns of the institutional investors. This same argument can be applied to the NSE because institutional investors hold the highest percentage of equity shares. Besides Waweru *et al*. (2008) find that the institutional traders' behaviour exhibits a psychological bias called herding (a tendency of institutions not to deviate from each other's investment decisions). There is also a positive and significant relationship between present and lagged returns when equal-weighted turnover is used as a measure of volume.

In terms of the robustness of the estimated models, the study employs Ljung-Box Q-Statistic to test for serial correlation in the residuals of each regression. The null hypothesis of no serial up to a higher lag of 5 is tested in all the SUR regressions. An examination of the Ljung-Box Q(5) statistic in Table 4.5 fails to reject the null hypothesis of no serial correlation.

In summary there is an indication that investor behaviour at the NSE is infested with the psychological bias of overconfidence. Although the overconfidence hypothesis predicts causality running from returns to trading volume as evidenced in this study's findings, one cannot conclude the existence of overconfidence by only running causality tests. Besides, there are trading volume theories that predict a similar result. It is for this reason that we test for self-attribution bias which depicts changes in observed overconfidence. Moreover, the self-attribution bias only holds in overconfidence theories.

4.2.4 Biased self-attribution Results

4.2.4.1 Testing the ARCH Effect

In here, we introduce ARCH/GARCH modelling with the aim of using its results to test biased self-attribution of investor behaviour in the NSE data. We begin by choosing an appropriate mean equation, established as an ARMA (1, 1) process whose choice is based on an information criterion. Appendix Table 1.12 section depicts the results of the mean equation whose residuals we employed in establishing ARCH effects and any remaining serial correlation.

This study employs two tests, namely the Ljung-Box-Q statistic and Engle's ARCH-LM test statistic to ascertain the presence of ARCH effect in the mean equation. In conducting the two tests, we use squared residuals that we obtain from the mean equation. We report the Ljung-Box Q-statistic results in Table 4.6 along with the autocorrelations, partial autocorrelations and the probability values corresponding to the various lags. The results for the Ljung-Box Q-statistic for all lags are significant at conventional levels. This is a pointer to the presence of ARCH effect and time-varying volatility in the NSE-20 share returns. In non-technical terms the results imply the ARCH-type of models are appropriate for use given the statistical properties of the NSE returns.

Table 4.6: ARCH effect test results using Ljung-Box Q-Statistic

Selected lags	AC	PAC	Q-Stat	P-Value
Lag 6	0.056	0.041	35.232	0.000
Lag 12	-0.016	-0.025	38.605	0.000
Lag 18	0.023	0.000	48.871	0.000
Lag 24	0.005	-0.012	54.826	0.000
Lag 30	-0.006	-0.015	55.180	0.002
Lag 36	-0.003	-0.061	61.745	0.002

Source: Extracted from Appendix Table 1.13

Further, Table 4.7 shows the ARCH-LM test results for Arch effects in the NSE-20 share index over the sample period. It is a regression of the squared residuals from the mean equation over the lagged squared residual values. Both the F-statistic and the LM- statistic, which are chi-square-distributed, are significant at 1% as evidenced by their p-values of 0.001 and 0.001 respectively. This high significance level suggests the presence of ARCH in the NSE-20 share returns and corroborates the Ljung-Box Q-statistic results in Table 4.6.

Table 4.7: ARCH-LM Test for Stock Returns on the NSE-20 Share Index

F- Statistics	5.291	Prob. F(5,490)	0.001
Obs*R-Squared	25.411	Prob. Chi-Square (5)	0.001

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.592	1.642	4.015	0.001
RESID^2(-1)	0.174	0.045	3.853	0.001
RESID^2(-2)	0.065	0.045	1.443	0.149
RESID^2(-3)	0.026	0.045	0.571	0.568
RESID^2(-4)	0.084	0.045	1.835	0.067
RESID^2(-5)	-0.024	0.045	-0.534	0.594
R-Squared	0.051			
Adj R-Squared	0.042			

Source: Author's computations.

Finally, testing for any serial correlation in the mean equation that we estimate as an ARMA (1, 1) process helps in showing that one has specified it well (the mean equation). A well specified mean equation carries two meanings in this study, namely- (i) that our conclusions on the ARCH effect are valid and (ii) the mean equation in the GARCH estimation process should be an ARMA (1, 1). The LM serial correlation test of the Breusch-Godfrey type indicates that we may not reject the null hypothesis of no serial correlation in the residuals of the specified mean equation. We present these results in Table 4.8.

Table 4.8: Breusch-Godfrey Serial Correlation LM test

F-Statistic	0.128	Prob. F(2, 496)	0.879
Obs*R-Squared	0.257	Prob. Chi-Square(2)	0.879

Test Equation:

Dependent Variable: RESID
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006	0.278	0.022	0.982
AR(1)	0.003	0.031	0.114	0.909
MA(1)	-0.008	0.044	-0.182	0.856
RESID(-1)	0.024	0.049	0.498	0.618
RESID(-2)	0.007	0.048	0.155	0.876
R-Squared	0.0005			
Adj. R-Squared	-0.007			

Source: Author's own calculations.

In summary, this section succeeds in showing that the NSE returns contain ARCH effects which support the application of the ARCH models. Further, in ascertaining the appropriate structure and lag length of the mean equation, the study establishes it as an ARMA (1, 1). This is so because the proposed structure of the mean equation contains no serial correlation as depicted by the Breusch-Godfrey LM test.

4.2.4.2 GARCH-Model Results

The rationale for presenting the symmetric and asymmetric GARCH model results is to ensure that the specification of both the mean and variance equations passes various test criteria. Additionally, well-specified GARCH models are important to this study because in constructing forecast errors or unexpected returns to test for biased self-attribution, we employ residuals from these (GARCH) models in running regression equation 3.6. In Table 4.9, we show the results for both the symmetric GARCH and asymmetric EGARCH and GJR-GARCH in which we specify them all as ARMA (1, 1) processes.

We start by filtering the conditional mean structure in the NSE data by estimating ARMA (p, q) models in which r_t (the NSE market) return is the dependent variable. We determine the AR (p) and MA (q) orders by using the AIC and zero in on an ARMA (1, 1) structure as the appropriate representation of the NSE-20 share returns. The results of the mean equations for all the three GARCH-type models presented in Table 4.9 show significant parameters at 1%, this means that the lagged values of returns and lagged errors affect the current NSE-20 share returns.

The different GARCH model results we present help in characterising conditional variance and volatility clustering inherent in the NSE market returns. We use an iterative procedure- the Marquardt algorithm in estimating the three GARCH-type models.

Table 4.9: GARCH family model results for the returns on the NSE-20 Share Index

	ARMA (1,1)-GARCH (1,1)	ARMA (1,1)- EGARCH (1,1)	ARMA (1,1)- GJR-GARCH(1,1)
Mean Equation			
c	-0.026	-0.077	-0.013

	(0.185)	(0.186)	(0.194)
	[0.886]	[0.676]	[0.947]
AR(1)	0.880	0.874	0.891
	(0.048)	(0.051)	(0.045)
	[0.000]*	[0.000]*	[0.000]*
MA(1)	-0.717	-0.714	-0.735
	(0.067)	(0.069)	(0.063)
	[0.000]*	[0.000]*	[0.000]*
Variance Equation			
ω	0.532	-0.083	0.499
	(0.235)	(0.066)	(0.225)
	[0.023]**	[0.207]	[0.026]**
f_1	0.201	0.343	0.194
	(0.058)	(0.081)	(0.075)
	[0.001]*	[0.000]*	[0.009]*
f_2	0.761	0.921	0.772
	(0.057)	(0.034)	(0.055)
	[0.000]*	[0.000]*	[0.000]*
κ		0.018	-0.005
		(0.047)	(0.091)
		[0.691]	[0.953]
Persistence	0.962	0.921	0.964
Log Likelihood	-1174.119	-1173.133	-1174.102
AIC	4.715	4.715	4.718
SC	4.774	4.782	4.786
HQC	4.738	4.741	4.745
N	501	501	501

Source: Author's calculations.
Notes:
(i) ( ) is for standard errors while [ ] is for probability values. * and ** indicate significance levels at 1% and 5% respectively.
(ii) AIC is Akaike Information Criterion, SC is Schwarz Criterion, HQC is the Hannan-Quinn Criterion and N shows the number of Observations

First, the ARMA (1, 1)-GARCH (1, 1) results indicate that both the ARCH (f_1) and GARCH (f_2) terms are statistically significant (at 1%) and positive. The sum of the two terms yields a value of 0.962 that is closer to unity; this is an indicator of persistence of volatility shocks.

A large GARCH term translates into persistence of volatility whereas a large ARCH term would mean that volatility is less persistent. Further, a summation of the ARCH and GARCH terms that yields a value of less than one implies that the volatility process is co-variance stationary or mean reverting. The intuition of such a result is that much as volatility takes a long time, it ultimately returns to the mean level of volatility.

Second, in capturing the asymmetric response of volatility to news or "leverage effect", we estimated ARMA (1, 1)-EGARCH (1, 1) and ARMA (1, 1)-GJR-GARCH (1, 1). In both models, the ARCH and GARCH parameters are positive and significant at 1%. The meaning of this is that both current news and old news have a great impact on the volatility level of the NSE returns. The persistence terms are 0.921 and 0.964 for the EGARCH and the GJR-GARCH respectively. These terms are evidences of volatility persistent processes that lead to past volatility to be reflected in the conditional variance. The fact that these terms are close to unity implies the existence of a high but stationary persistence of conditional variance. In addition, the asymmetric term κ does not give statistically significant results in both models. This means that we find no evidence of the "leverage effect" in the weekly returns of the NSE.

The GARCH-family results described in this study are in agreement with Nyamongo and Misati (2010) in several ways and are comparable to Obere (2009). Nyamongo and Misati (2010) find that the volatility of the NSE equities returns is highly persistent, the "leverage effects" are not significant; and the impact of news on volatility is not significantly asymmetric. Our study confirms the above findings since we are able to detect persistence in the weekly returns series of the NSE, and insignificant asymmetric impact of news on volatility. There is evidence of asymmetry in the returns of individual stocks that constitute the NSE-20 share index as illustrated in Obere (2009). This finding means that big changes in returns follow big ones, small changes follow small ones, and negative changes in returns are more persistent than positive changes. We are unable to draw such a conclusion when we consider the market returns data.

The purpose of estimating the various forms of GARCH models is to use their residuals to proxy investor forecasts at the NSE. The symmetric ARMA (1, 1) – GARCH (1, 1) along with the asymmetric ARMA (1, 1) – EGARCH (1, 1) and ARMA (1, 1) – GJR-GARCH (1, 1) results are presented. However, since the symmetric GARCH model treats both positive and negative shocks uniformly, it is not appropriate to use in generating investor forecasts that proxy investor behaviour.

The behaviour of investor behaviour follows asymmetric GARCH models that treat positive and negative shocks differently. This is in line with the biased self-attribution theory that asserts that current higher positive returns are followed by higher trading because individuals think that they made right predictions or decisions in the previous period. For current negative returns, their confidence goes down by a small level because they do not believe that they made wrong forecasts in the previous period.

Consequently, the choice of the asymmetric GARCH models over the symmetric ones is justifiable mainly from a theoretical rather than a statistical view point. The study uses the residuals of the EGARCH and GJR-GARCH to derive the forecasts of equation 3.6. However diagnostic tests (see Table 4.10) on the said GARCH models are in order for it is important to establish if they are well-specified.

4.2.4.3 Diagnostic Checks on the GARCH models

The diagnostic tests conducted in Table 4.10 are based on three tests; first, the Ljung-Box Q-statistics of the standardised residuals, second the Ljung-Box Q-Statistics of the squared standardised residuals and finally the ARCH LM-test. The purpose of the Ljung-Box Q-test Statistics (1) is to test for the remaining autocorrelation in the standardised residuals of the mean equations across all the GARCH-type models. The results indicate that the autocorrelations of the standardised residuals are insignificant for all lags and models. This confirms the absence of autocorrelation in the standardised residuals, which is an indication of well-specified mean equations.

Further, the Ljung-Box Q-test Statistics (2) tests for ARCH effects in the squared standardised residuals of the variance equation. The corresponding $p-values$ for all lags across all models are insignificant; hence, a confirmation of absence of additional ARCH effects in the specified variance equations. The ARCH – LM test statistics for all the models that start from lag 1 to 5 confirms the absence of additional ARCH effects in the standardised residuals of the variance equations and this is supported by the statistically insignificant $p-values$.

Table 4.10: Diagnostic Checks of the GARCH-family models: Ljung-Box Q-statistics and the ARCH-LM test of 0rder 5

	Ljung-Box Q- Statistic(1)				Ljung-Box Q-statistic(2)				ARCH LM- Test	
	Q(5)	Q(10)	Q(15)	Q(20)	Q(5)	Q(10)	Q(15)	Q(20)	F	$N*R^2$
ARMA (1,1)- GARCH (1,1)	4.975 (0.174)	10.263 (0.247)	13.114 (0.439)	15.046 (0.659)	3.043 (0.385)	7.486 (0.485)	13.662 (0.398)	15.738 (0.611)	0.615 (0.688)	3.092 (0.685)
ARMA (1,1)- EGARCH (1,1)	4.786 (0.188)	10.448 (0.235)	13.441 (0.414)	15.300 (0.641)	2.456 (0.483)	6.199 (0.625)	12.445 (0.491)	13.589 (0.755)	0.487 (0.785)	2.457 (0.783)
ARMA (1,1)- GJR-GARCH (1,1)	5.152 (0.161)	10.388 (0.239)	13.124 (0.438)	15.008 (0.661)	2.946 (0.400)	6.987 (0.538)	13.201 (0.432)	15.251 (0.645)	0.592 (0.706)	2.976 (0.704)

Source: Extracted from Appendix Tables 1.14, 1.15, 1.16, 1.17, 1.18 and 1.19.

Notes:

(i) Ljung-Box Q- Statistic(1) tests for the joint significance of remaining autocorrelation in the standardised residuals of the mean equations while Ljung-Box Q-statistics(2) tests for additional ARCH effect in the squared standardised residuals of the variance equation. It can also be viewed as a joint significance test of no autocorrelation in the standardised squared residuals up to the specified lag.

(ii) The ARCH LM (5) tests the null hypothesis of no ARCH effect in the standardised squared residuals for lags 1 to 5.

(iii) The figures in the parentheses are $p-values$. We display the AC, PAC, Q-statistics and their corresponding $\rho-values$ in the Appendix Tables 1.14, 1.15, 1.16, 1.17, 1.18 and 1.19 from lag 1 up to lag 36.

4.2.4.4 Results of self-attribution bias

The framework of comprehending the self-attribution bias lies in the relationship between trading volume and stock market returns conditional on investors' right and wrong forecasts. Table 4.11 presents the results of this relationship following a regression estimation of equation 3.6. In this regression, the coefficients β_j measure the effect of investor overconfidence on trading volume when investors make right forecasts whereas the coefficients γ_j measure the effect of investor overconfidence when they make wrong forecasts.

The results show a mixed scenario in which some estimated β_j and γ_j coefficients are individually significant whereas others are not. When one applies the statistical restrictions implied in the estimated model vis-à-vis the self-attribution bias theory, one is able to notice that the sum of $\beta_j 's$ for both the value and equal-weighted turnover series are positive and significant at conventional levels. Specifically, the sum of $\beta_j 's$ for equal and value-weighted volume when we use residuals from the EGARCH model to construct investors' forecasts is 0.017 and 0.005 respectively. The corresponding values when the residuals are derived from the GJR-GARCH models are 0.017 and 0.006 for the equal and value-weighted turnover respectively. The $p-values$ corresponding to the $\chi^2_{\beta(1)}$ statistics used in testing the null hypothesis that the sum of β_j is not significantly different from zero indicate that the null hypothesis can be rejected at conventional levels. This result means that when investors attribute past market gains to their own ability of making right forecasts, they trade more in the subsequent periods.

Table 4.11: Regression results between turnover and stock returns conditional on investors' forecasts

Source of μ_t and η_t	ARMA (1,1)-EGARCH (1,1)		ARMA (1,1)- GJR-GARCH (1,1)	
Dependent Variable	v_{1t}^{ew}	v_{1t}^{vw}	v_{2t}^{ew}	v_{2t}^{vw}
$\beta_1 (p-value)$	0.009 (0.001)*	0.003 (0.001)*	0.009 (0.004)*	0.003 (0.006)*
$\beta_2 (p-value)$	0.004 (0.021)**	0.001 (0.033)**	0.004 (0.022)**	0.002 (0.033)**
$\beta_3 (p-value)$	0.004 (0.034)**	0.001 (0.194)	0.004 (0.033)**	0.001 (0.182)
$\gamma_1 (p-value)$	0.002 (0.265)	0.001 (0.273)	0.002 (0.248)	0.001 (0.249)
$\gamma_2 (p-value)$	-0.002 (0.348)	-0.001 (0.903)	-0.002 (0.282)	-0.001 (0.824)
$\gamma_3 (p-value)$	-0.004 (0.054)***	-0.001 (0.197)	-0.004 (0.029)**	-0.001 (0.134)
$\lambda_1 (p-value)$	0.018 (0.003)*	0.007 (0.007)*	0.018 (0.005)*	0.007 (0.011)**
$\lambda_2 (p-value)$	0.006 (0.271)	0.000 (0.991)	0.006 (0.217)	0.001 (0.915)
$\lambda_3 (p-value)$	0.008 (0.138)	0.001 (0.561)	0.008 (0.121)	0.001 (0.541)
$\beta_1 + \beta_2 + \beta_3$	0.017	0.005	0.017	0.006
$\chi^2_{\beta(1)} (p-value)$	31.042 (0.000)*	25.022 (0.000)*	31.618 (0.000)*	25.554 (0.000)*
$\chi^2_{\beta(2)} (p-value)$	31.669 (0.000)*	26.702 (0.000)*	32.317 (0.000)*	27.148 (0.000)*
$\gamma_1 + \gamma_2 + \gamma_3$	-0.004	-0.001	-0.004	-0.001
$\chi^2_{\gamma(1)} (p-value)$	0.744 (0.388)	0.024 (0.877)	1.075 (0.299)	0.077 (0.781)
$\chi^2_{\gamma(2)} (p-value)$	4.686 (0.196)	2.927 (0.403)	5.613 (0.132)	3.659 (0.301)
$\lambda_1 + \lambda_2 + \lambda_3$	0.033	0.008	0.034	0.008
$\chi^2_{\lambda(1)} (p-value)$	9.096 (0.003)*	3.336 (0.067)***	9.223 (0.002)*	3.112 (0.077)***
$\chi^2_{\lambda(2)} (p-value)$	12.104 (0.007)*	9.713 (0.021)**	11.563 (0.009)*	8.715 (0.033)**
$\chi^2_{\beta\gamma} (p-value)$	15.438 (0.001)*	8.547 (0.003)*	17.705 (0.000)*	9.718 (0.002)*
$\overline{R}^2$	0.195	0.108	0.200	0.110
AIC	-1.901	-3.448	-1.906	-3.451
SC	-1.807	-3.355	-1.813	-3.357
HQC	-1.863	-3.412	-1.869	-3.414

Source: Author's calculations based on regression results in Appendix Tables 1.20, 1.21, 1.22 and 1.23; it is equation 3.6 below that yields the above results. $v_{xt} = \alpha_0 + \alpha_1 r_t + \sum_{j=1}^{p} \beta_j (r_{t-j} \times I_{t-j}) + \sum_{j=1}^{p} \gamma_j (r_{t-j} \times (1 - I_{t-j})) + \sum_{j=1}^{p} \lambda_j |\eta_{t-j}| + \varepsilon_t$

Notes:

(i) We make use of Newey and West (1987) procedure to correct for heteroskedasticity and autocorrelation in the standard errors.

(ii) We employ the Wald test statistic that is asymptotically chi-squared distributed with degrees of freedom equal to the number of restrictions imposed in different cases in order to test various hypotheses. Specifically, $\chi^2_{\beta(1)}$, $\chi^2_{\gamma(1)}$ and $\chi^2_{\lambda(1)}$ test the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$, that $\gamma_1 + \gamma_2 + \gamma_3 = 0$ and that $\lambda_1 + \lambda_2 + \lambda_3 = 0$, respectively. Additionally, $\chi^2_{\beta(2)}$, $\chi^2_{\gamma(2)}$ and $\chi^2_{\lambda(2)}$ test statistic test the null hypothesis that $\beta_j = 0$ for all j, that $\gamma_j = 0$ and that $\lambda_j = 0$, for all j respectively. Finally, the $\chi^2_{\beta\gamma}$ test statistic tests the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = \gamma_1 + \gamma_2 + \gamma_3$.

(iii) *, ** and *** represent 1%, 5% and 10% significance levels respectively.

Further, this study finds that $\sum_{j=1}^{3}\beta_j > \sum_{j=1}^{3}\gamma_j$ for all cases of trading volume and besides the $\chi^2_{\beta(\gamma)}$ test statistic used to test the null hypothesis that is $\sum_{j=1}^{3}\beta_j = \sum_{j=1}^{3}\gamma_j$ is rejected at all conventional levels in both the equal and value-weighted turnover series. The fact that $\sum_{j=1}^{3}\beta_j > \sum_{j=1}^{3}\gamma_j$ and the rejection of the hypothesis that $\sum_{j=1}^{3}\beta_j = \sum_{j=1}^{3}\gamma_j$ provides further empirical support of self-attribution bias in investor behaviour at the NSE. Chuang and Lee (2006) whose estimation techniques are similar to this study's, establish a similar result using data of the AMEX. The intuition of our study's result is that, investors at the NSE exhibit overconfidence that generates higher trading when they make gains in the market having gotten their forecasts of future stock returns right than as they make wrong forecasts.

One significant difference between Chuang and Lee (2006) empirical findings and that of this study is that in the former the sum of the coefficient depicting investors' wrong forecasts (γ_j) for all the various trading volume series is statistically different from zero whereas the reverse is true in the latter case. However, in both cases, the γ_j coefficients are jointly statistically not different from zero. The intuition behind this result vis-à-vis the self-attribution bias is that investors are not likely to attribute any negative returns to their failure to predict and interpret the current market signals. In other words, when they make losses their overconfidence does not significantly decline to affect trading volume.

The coefficient λ_j that depicts the effect of the precision of investors' forecasts on their overconfidence shows results that are slightly different from this study's expectations. One would expect that in the presence of self-attribution bias that leads to higher trading, the precision of the investors' forecasts would be highly improved. In other words, there would be a negative relation between turnover and the precision of investors' forecasts. The results indicate that the sum of all $\lambda_j s$ for both equal and value-weighted turnover is positive and significant at conventional levels. In addition, all the values of λ_j are jointly significantly different from zero at conventional test sizes. The meaning of these results is that the degree of investor overconfidence in a frontier market like that of NSE does not depend on the precision of their forecasts of future stock returns. This result contrasts with that of Chuang and Lee (2006) who established weak evidence that the degree of overconfidence depends on the precision of investors' forecasts of future stock returns in the developed markets of the United States.

Conclusively, our study confirms the presence of self-attribution bias in investor behaviour at the NSE, which is a frontier market, just as Chuang and Lee (2006) established such behaviour in the American stock exchange data. Even if investors at the NSE make highly imprecise forecasts of future stock returns, their level of overconfidence is not affected. This is the evidence that the NSE market level data depicts in this study.

4.2.5 Overconfidence and volatility Results

We report the results relating overconfidence and conditional volatility in Table 4.12. The generation of the results in Table 4.12 is a result of the augmentation of the ARMA (1, 1) -

GARCH (1, 1) and the ARMA (1, 1) – GARCH (1, 1) with $OVER_t$ and $NONOVER_t$ that represent trading volume associated with past stock returns (overconfidence) and trading volume that is not related to past stock returns (overconfidence) respectively.

Table 4.12: Regression results between conditional volatility of stock returns and trading volume

Model	ARMA(1,1)- GARCH(1,1)		ARMA(1,1)- EGARCH(1,1)	
Conditional Volatility	h_t		$\ln h_t$	
Trading Volume	v_{1t}^{ew}	v_{1t}^{vw}	v_{2t}^{ew}	v_{2t}^{vw}
$\omega(p-value)$	1.415 (0.006)*	1.657 (0.002)*	-0.049 (0.767)	0.053 (0.221)
$f_1(p-value)$	0.346 (0.001)*	0.401 (0.001)*	0.157 (0.002)*	0.154 (0.002)*
$f_2(p-value)$	0.542 (0.000)*	0.478 (0.000)*	0.969 (0.000)*	0.973 (0.000)*
$f_3(p-value)$	7.316 (0.045)**	22.912 (0.019)**	0.656 (0.001)*	1.416 (0.001)*
$f_4(p-value)$	12.754 (0.533)	33.824 (0.596)	-14.607 (0.000)*	-43.16 (0.000)*
$\kappa(p-value)$			0.469 (0.000)*	0.485 (0.000)*
Log likelihood	-1168.9	-1168.9	-1161.5	-1162.0
$Q(12)(p-value)$	12.576 (0.248)	12.763 (0.237)	8.477 (0.582)	8.543 (0.576)
$Q(24)(p-value)$	16.975 (0.765)	17.181 (0.753)	14.434 (0.885)	15.274 (0.850)
$Q(36)(p-value)$	30.157 (0.657)	32.015 (0.565)	25.512 (0.853)	26.642 (0.812)
$Q^2(12)(p-value)$	9.368 (0.498)	9.277 (0.506)	13.705 (0.187)	13.229 (0.211)
$Q^2(24)(p-value)$	22.423 (0.435)	22.738 (0.417)	21.138 (0.512)	22.183 (0.449)
$Q^2(36)(p-value)$	35.146 (0.414)	36.012 (0.374)	31.036 (0.614)	34.362 (0.450)
$\chi_1^2(p-value)$	0.065 (0.797)	0.027 (0.868)	48.261 (0.000)*	47.879 (0.000)*

Source: Author's estimations based on ARMA (1, 1)-GARCH (1, 1) and ARMA (1, 1) - EGARCH (1, 1).
Notes:
(i) Specifically, we estimated the following regressions,

3.8
$$r_t = \mu_t + \eta_t,$$
$$\eta_t \mid (v_t, \eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t),$$
$$h_t = \omega + f_1(\eta_{t-1}^2) + f_2 h_{t-1} + f_3 NONOVER + f_4 OVER_t,$$

3.9
$$r_t = \mu_t + \eta_t,$$
$$\eta_t \mid (v_t, \eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t),$$
$$\ln h_t = \omega + f_1\left(\frac{|\eta_{t-1}| + \kappa\eta_{t-1}}{\sqrt{h_{t-1}}}\right) + f_2 \ln h_{t-1} + f_3 NONOVER_t + f_4 OVER_t,$$

(ii) As a diagnostic check, we employ the Ljung-Box Q-statistics that tests for autocorrelation from the first lag up to the last lag that is 36 in this case. Specifically, Q (12), Q (24) and Q(36) test the joint significance of autocorrelations up to specified lags in the standardised residuals whereas Q^2 (12), Q^2(24) and Q^2(36) test for joint autocorrelations in the standardised squared residuals.

(iii) To test the null hypothesis that $f_3 = f_4$ we employ the Wald test that is χ^2 with one degree of freedom and corresponding $p-values$.

(iv) $*$ and $**$ represent 1% and 5% significance levels respectively.

The results indicate significant ARCH and GARCH effects across all the four estimated models. Specifically, the ARCH and GARCH coefficients f_1 and f_2 respectively are statistically significant at all conventional levels an indication that the impact of old news on volatility is significant at the NSE.

There are mixed results relating overconfidence and conditional volatility. The ARMA (1, 1) - GARCH (1, 1) results suggest that the $OVER_t$ coefficient f_4 is greater than the $NONOVER_t$ coefficient f_3 as predicted by the overconfidence theory. Much as this is the case that $f_4 > f_3$, the f_4 coefficients are not significantly different from zero whereas those of f_3 are significantly different from zero at 5% level. This result gives two interpretations- first, there is weak evidence that market volatility is partly due to investor overconfidence and secondly, there is a stronger case for other factors other than investor overconfidence in causing observed market volatility at the NSE.

Turning to the ARMA (1, 1) - EGARCH (1, 1), both the $NONOVER_t$ and $OVER_t$ coefficients f_3 and f_4 respectively are significant at all conventional levels. This is a further indication that both the overconfidence-based trading as well as the other factors that do not relate to overconfidence significantly affects conditional volatility at the NSE. This discovery is similar to Chuang and Lee (2006) result with the only difference being in the negative sign that the coefficient f_4 takes in this study. Hence, it turns out that $f_3 > f_4$ which means that factors that are unrelated to past stock returns (overconfidence) count more in bringing about excess volatility than overconfidence-based trading.

In testing the null hypothesis that there is no difference between overconfidence-based volume and volume that is not supported by overconfidence in relation to excess volatility, we employ the Wald test that is chi-squared distributed with one degree of freedom. Specifically, we test the null hypothesis that $f_3 = f_4$. Table 4.12 reports the results obtained when the above null hypothesis is tested using the chi-square values (χ_1^2) with the corresponding $p-values$. The results indicate that with the ARMA (1, 1) – GARCH (1, 1) model, the hypothesis may not be rejected where as with the ARMA (1, 1) – EGARCH (1, 1) model the hypothesis that $f_3 = f_4$ is rejected. We attribute this difference to the fact that the former model is symmetric by nature whereas the later one accounts for asymmetry in the impact of positive and negative news on volatility.

A diagnostic check on the standardised residuals and squared standardised residuals following specifications of the mean and variance equations of the GARCH-family models is conducted in order to test for presence of any autocorrelation. We employed the Ljung-Box Q- Statistics whose results are reported in Table 4.12 for lags 1 up to 36. We find no evidence for autocorrelation in all the residuals which is a signal that our models are well specified.

In conclusion this study establishes two sets of results relating volatility and overconfidence. First, conditional volatility at the NSE is caused by both overconfidence-based trading and other factors unrelated to overconfidence. Nevertheless, the asymmetric EGARCH model that this study employs indicates that trading unrelated to overconfidence performs better in explaining conditional volatility than over-based trading. Secondly, since the study (through the GARCH) rejects the hypothesis that $f_3 = f_4$, it means that the NSE's trading volume indeed has a component that is due to overconfidence-based trading and another one that is explainable by other factors. And it is actually the case that the two affect conditional volatility at the NSE.

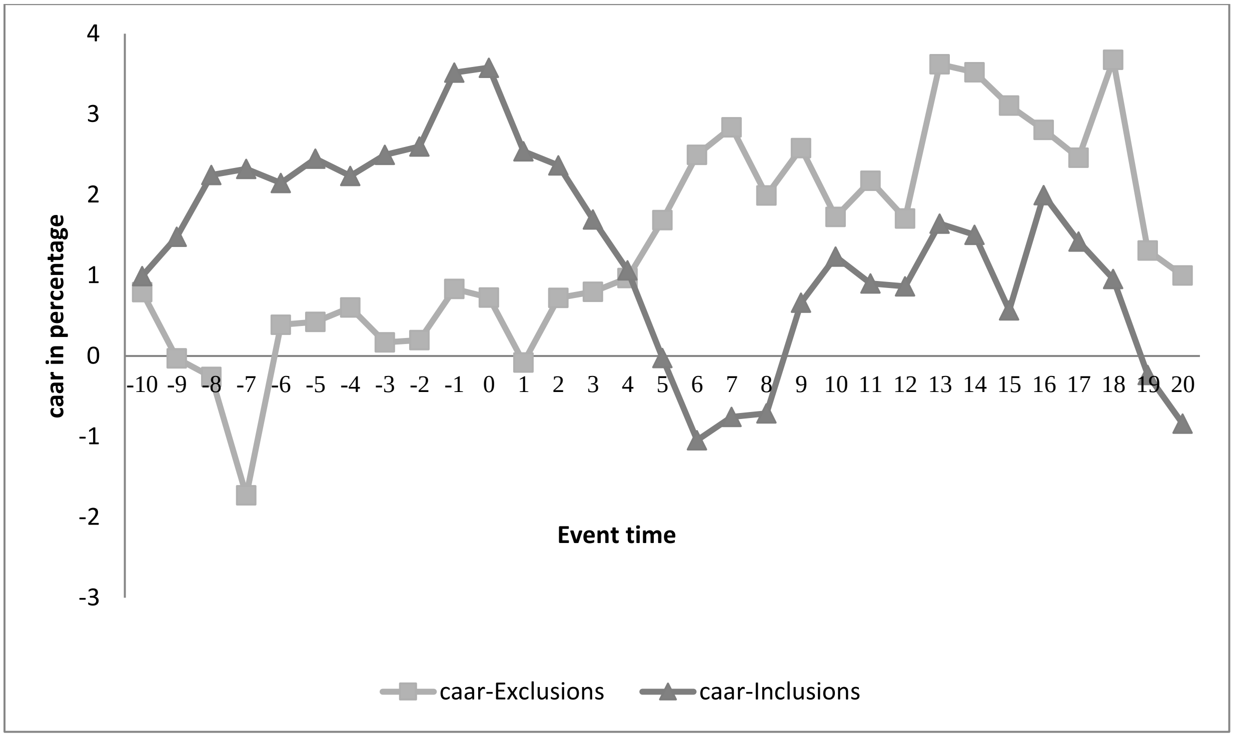
4.3 Findings pertaining to index revisions at the NSE

The empirical results that are discussed in this section fall into two categories which include the graphical illustrations as well as the event study methodology. The graphical approach comes first and it is followed by the tabulated event study results. However, this does not mean that they represent different ideas but rather support each other.

4.3.1 Graphical results to index inclusions and exclusions

Figure 4.3 depicts the cumulative average abnormal returns ($caar$) that are generated when the OLS market model is employed in estimating the normal returns in order to ascertain the abnormal returns.

Figure 4.3: OLS Market model-generated Cumulative average abnormal returns for both inclusions and exclusions



From Figure 4.3, the event window period runs from 10 days prior to the effective change date to 20 days after the revision takes place. The date when the actual change takes place denoted $t = 0$ is referred to as the "change date" or "effective change date". The purpose of the first 10 days before the change in the market index is effected is to show if the change was anticipated or not. In other words, it is intended to capture the trading behaviour in the two weeks that precede the index revision at the NSE.

An examination of the stocks included into the NSE-20 share index reveals that there is an increase in the *caar* starting 5 days before the actual change takes place. Specifically, at day -5, the cumulative average abnormal returns (*caar*) increase from 2.14 percent to 2.44

percent, marginally reduce to 2.23 percent on day -4 and thereafter continue rising to 2.49 percent, 2.60 percent, 3.5 percent and 3.57 percent on days -3, -2, -1 and 0 respectively.

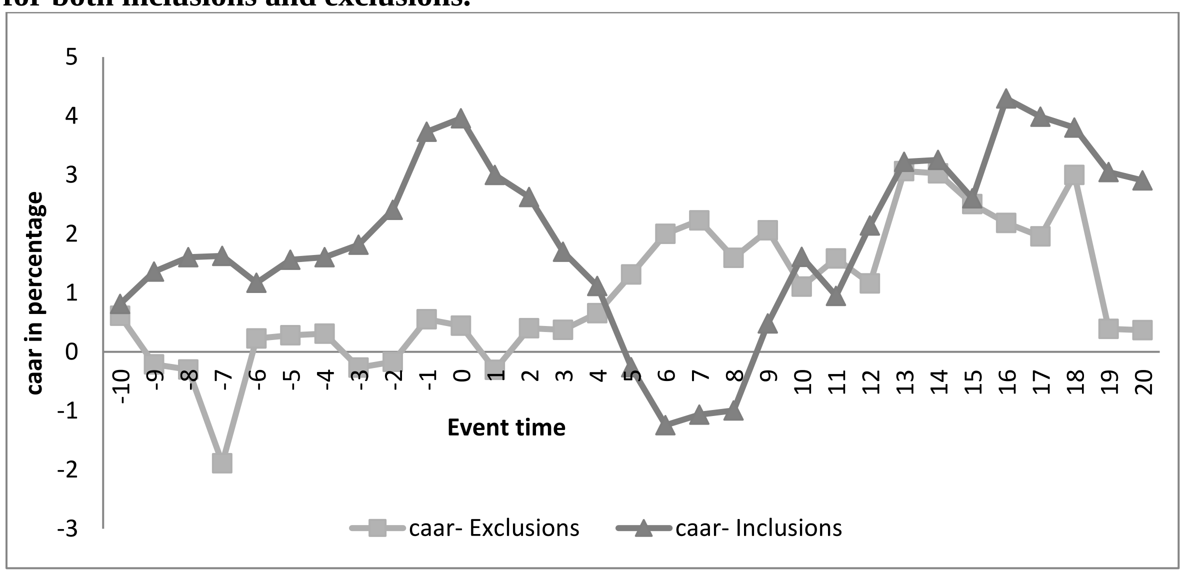
A further examination of the *caar* in Figure 4.3 reveals that the highest values are registered one day before the inclusion (that is 3.51 percent) and on the actual date of the inclusion (that is 3.57 percent). The days that follow the actual change date witness positive but declining *caar* up to day 5 when they become and remain negative up to day 8. All through this period, the *caar* are less than those witnessed on the actual event date.

Turning to the graph of the excluded stocks in Figure 4.3, it does not show a remarkable asymmetry with that of the included stocks as predicted by the PPH. The pre-change date period (-10 to -1) depicts mixed results. There is a general decline starting from day -10 to day -7 which is followed by a sharp rise on day -6 plus a mild rise up to day -4. Further, it is noticeable that the *caar* decline from day -1 (a day before the change date) through the event day 0 and eventually becoming negative one day after the change date- a result that is predicted by the PPH.

From the graphical presentation in Figure 4.3, it is difficult to visualise the index effects as predicted in the PPH. However, what is evident so far is that there are some observable price effects especially during and immediately after the change date in both inclusions and exclusions. The issue of their statistical significance is what we tackle when we present the tabulated cumulative average abnormal returns hereafter.

Studies examining share prices in frontier and emerging stock markets are susceptible to yielding biased results due to the thin trading problem. Hence, the argument that the cumulative average abnormal returns observed in Figure 4.3 which were generated through the market model are suspect is addressed by running a parallel market model that controls for thin trading. It is against this background that we present the graphed Dimson market model results in Figure 4.4 to check if they are significantly different from the market model ones.

Figure 4.4: Dimson's market model-generated cumulative average abnormal returns for both inclusions and exclusions.



The results in Figure 4.4 show some level of consistency with those in Figure 4.3 at least in terms of the signs that the *caar* assume in almost all cases. The major difference in both inclusions and exclusions lies in the size/magnitude of the *caar*. Nevertheless, the movements in both cases are similar which means that both the market and Dimson models perform a similar job in capturing the price effects following the revision of the NSE-20 share index. We supplement the graphical presentations with the tabulated results that display the levels of statistical significance of the cumulative average abnormal returns.

4.3.2 The Event Study Results for Index inclusions

The testing of the null hypothesis that index inclusions do not lead to abnormal returns is conducted based on the results presented in Table 4.13. The table presents the results of cumulative average abnormal returns ($caar$) generated through two models- the OLS market model and the Dimson aggregated coefficients market model.

The estimates of the $caar$ under the OLS market model indicate a positive increase in the period prior to the change date though it (the increase) is not statistically significant. The value of the $caar$ on the change date is 3.58 percent and it is the highest throughout the event window period, however its corresponding t-value of 0.378 signals statistical insignificance. The days following the event date register a decline in the $caar$ values up to day 10 and thereafter the market witnesses mixed results (increases and decreases) up to day 20. However, throughout this period, the t-values remain low thereby signalling statistical insignificance of the abnormal returns that emerge when new stocks enter the NSE-20 share index.

Table 4.13: Cumulative average abnormal returns for index inclusions

	OLS Market Model			Dimson's aggregated coefficients market model		
Event time	aar	caar	t-statistic	aar	caar	t-statistic
-10	0.0099	0.0099	0.1072	0.0081	0.0081	0.0968
-9	0.0049	0.0148	0.1602	0.0055	0.0136	0.1616
-8	0.0077	0.0225	0.2433	0.0024	0.0160	0.1905
-7	0.0008	0.0232	0.2515	0.0002	0.0163	0.1933
-6	-0.0017	0.0215	0.2326	-0.0045	0.0117	0.1394
-5	0.0030	0.0245	0.2651	0.0039	0.0156	0.1854
-4	-0.0021	0.0223	0.2420	0.0004	0.0160	0.1906
-3	0.0026	0.0250	0.2704	0.0021	0.0182	0.2160
-2	0.0010	0.0260	0.2816	0.0059	0.0241	0.2865
-1	0.0092	0.0352	0.3807	0.0132	0.0373	0.4437
0	0.0006	0.0358	0.3876	0.0023	0.0396	0.4709
1	-0.0104	0.0254	0.2751	-0.0096	0.0300	0.3568
2	-0.0017	0.0237	0.2563	-0.0038	0.0263	0.3122
3	-0.0067	0.0170	0.1837	-0.0093	0.0170	0.2019
4	-0.0063	0.0106	0.1152	-0.0058	0.0112	0.1329
5	-0.0109	-0.0003	-0.0028	-0.0138	-0.0026	-0.0311
6	-0.0102	-0.0105	-0.1132	-0.0098	-0.0124	-0.1478
7	0.0029	-0.0075	-0.0817	0.0018	-0.0107	-0.1267
8	0.0004	-0.0071	-0.0772	0.0007	-0.0099	-0.1180
9	0.0138	0.0066	0.0719	0.0148	0.0048	0.0575
10	0.0057	0.0124	0.1338	0.0113	0.0161	0.1914
11	-0.0033	0.0090	0.0976	-0.0066	0.0095	0.1128
12	-0.0004	0.0086	0.0935	0.0119	0.0214	0.2546
13	0.0078	0.0164	0.1777	0.0108	0.0322	0.3832
14	-0.0014	0.0151	0.1630	0.0003	0.0326	0.3871
15	-0.0094	0.0057	0.0615	-0.0066	0.0260	0.3091
16	0.0143	0.0200	0.2163	0.0169	0.0429	0.5104
17	-0.0058	0.0142	0.1537	-0.0031	0.0399	0.4740
18	-0.0046	0.0096	0.1036	-0.0018	0.0380	0.4521
19	-0.0119	-0.0024	-0.0256	-0.0076	0.0305	0.3621
20	-0.0060	-0.0084	-0.0910	-0.0014	0.0291	0.3454

Source: Author’s computations.

To ensure the robustness of the OLS market model results, an alternative market model of the Dimson type is estimated and its results are juxtaposed with those of the market model in Table 4.13. The results that follow Dimson's aggregated coefficients model are not any different from those of the market model in terms of signs and magnitude. For example, the value of the change date *caar* under the Dimson model is 3.96 percent whereas it is 3.58 percent under the OLS market model. More to that, there is a gradual increase in the cumulative average abnormal returns starting at day-5 up to the event day and thereafter a gradual decline up to day 5. Starting from day 6 onwards, there is an unpredictable movement in the values of the *caar*. Nevertheless, just like in the OLS market model case, the results under the Dimson method are also statistically insignificant.

Previous studies that have tested the stock inclusions in developed markets report significant positive cumulative average abnormal returns on the event day and the 2 weeks following the actual change. Specifically, Harris and Gurrel (1986) and Jain (1987) report positive significant abnormal returns on the event day and immediately after, but these die out (that is, the prices of the affected securities decline). For Shleifer (1986) and Kaul *et al*. (2000), they report a permanent significant increase in the prices of the affected securities on the event day and thereafter. This study yields increased *caar* results during index inclusions although they are statistically insignificant. Besides, it is difficult to point out any clear cut price reversals that follow the event day increase in the *caar* because the t-values are insignificant all through.

The uniqueness of this study's results regarding index inclusions could be attributed to the market-specific features in frontier markets that differ from those in developed markets. One possibility as to why the NSE fails to register significant cumulative average abnormal returns could be due to the absence of index fund managers following the market index. As Pruitt and Wei (1989) argue that markets with no significant number of index funds experience lower abnormal return changes than those with many index funds. Even in the presence of institutional investors whose activities proxy those of index funds, they (institutional investors) are unable to impact price movements the way index funds would when index inclusions take place. This is the case with the NSE where the majority of investors are institutions. Additionally, the small nature of the market relative to the developed markets yields a small sample of stocks and fewer events to study. Event studies do not perform so well with a small number of sample events.

This study's results in the case of inclusions are only similar to those attributed to Shankar and Randhawa (2006) who find no significant price effects following additions of stocks to the Straits Times Index (STI) of Singapore and the days after this event. A comparison of the price effects in the Singapore market with that of the Hong Kong one reveals that in the former case where there is a single index fund tracking the index, the price effects are insignificant unlike in the latter where there are many index funds. A similar argument holds in the case of the NSE where there are no index funds operating. Hence, the price effects witnessed in developed markets following inclusions are due to the demand-supply disequilibrium caused by large index funds and not new information contained in the event.

Additionally, the results that this study on index inclusions provides offer some dimensions about the efficiency of the NSE market. This argument finds backing from Brown and Warner (1980) who assert that event studies provide a direct test of market efficiency since systematically nonzero abnormal security returns that persist after a particular type of event are inconsistent with the hypothesis that share prices adjust quickly to fully reflect new information. The study's results reveal no significant abnormal returns following inclusions hence the market exhibits market efficiency in the weak form.

In conclusion, the NSE depicts an increase in the *caar* results on the inclusion of new stocks into the NSE-20share index. However, this increase is not statistically significant like in the case of developed markets. Consequently, conclusions on whether the witnessed price effects follow the PPH or ISH theories are inconclusive due to the lack of statistical significance in the *caar* results.

4.3.3 The Event Study Results for Index Exclusions

Table 4.14 depicts *caar* estimates with their corresponding t-values for the sample of stocks excluded from the NSE-20 share index. The value of the *caar* on the event day using the OLS market model is 0.73 percent with a corresponding t-value of 0.123 which is statistically insignificant. The 10 day period that precedes the actual change date depicts mixed results that is statistically insignificant increases and decreases in the *caar* estimates but with no clear patterns. The fact that the results in this period are not significant means two things- investors were not able to predict the change and even after the announcement of the change was made it never affected the market returns.

One can further note that the *caar* on day -1 is higher than the *caar* on the event day (day 0). In other words there is an observable decline in the *caar* when the actual exclusion takes place. Specifically, the *caar* declines from 0.83 percent on day -1 to 0.73 percent on the event day, and further declining to -0.08 percent on day 1. After this, it shows upward and downward movements that do not follow a particular trend. What cannot be dismissed though is the observed decline in the abnormal returns following the exclusion of some stocks from the market index as predicted by the PPH and ISH.

Table 4.14: Cumulative average abnormal returns for index exclusions

	OLS Market Model			Dimson's aggregated coefficients market model		
Event time	aar	caar	t-statistic	aar	caar	t-statistic

-10	0.0079	0.0079	0.1345	0.0061	0.0061	0.1184
-9	-0.0082	-0.0003	-0.0049	-0.0082	-0.0021	-0.0411
-8	-0.0023	-0.0026	-0.0439	-0.0009	-0.0030	-0.0581
-7	-0.0147	-0.0173	-0.2933	-0.0159	-0.0189	-0.3662
-6	0.0212	0.0039	0.0655	0.0211	0.0023	0.0437
-5	0.0004	0.0042	0.0719	0.0006	0.0028	0.0547
-4	0.0018	0.0060	0.1022	0.0002	0.0031	0.0595
-3	-0.0043	0.0017	0.0285	-0.0057	-0.0027	-0.0515
-2	0.0003	0.0020	0.0335	0.0010	-0.0017	-0.0323
-1	0.0063	0.0083	0.1410	0.0072	0.0055	0.1072
0	-0.0010	0.0073	0.1232	-0.0011	0.0044	0.0860
1	-0.0081	-0.0008	-0.0139	-0.0075	-0.0031	-0.0595
2	0.0080	0.0072	0.1222	0.0071	0.0040	0.0775
3	0.0007	0.0080	0.1349	-0.0003	0.0037	0.0723
4	0.0017	0.0097	0.1639	0.0028	0.0066	0.1271
5	0.0072	0.0169	0.2859	0.0066	0.0131	0.2545
6	0.0081	0.0250	0.4233	0.0069	0.0200	0.3883
7	0.0034	0.0284	0.4811	0.0023	0.0223	0.4330
8	-0.0084	0.0199	0.3381	-0.0064	0.0159	0.3090
9	0.0059	0.0258	0.4373	0.0047	0.0206	0.3998
10	-0.0085	0.0173	0.2925	-0.0096	0.0111	0.2145
11	0.0045	0.0218	0.3688	0.0048	0.0159	0.3076
12	-0.0047	0.0171	0.2893	-0.0043	0.0116	0.2249
13	0.0191	0.0362	0.6136	0.0191	0.0306	0.5947
14	-0.0010	0.0352	0.5974	-0.0004	0.0302	0.5869
15	-0.0041	0.0311	0.5271	-0.0052	0.0251	0.4867
16	-0.0030	0.0281	0.4757	-0.0032	0.0219	0.4242
17	-0.0034	0.0246	0.4175	-0.0023	0.0196	0.3802
18	0.0121	0.0368	0.6232	0.0104	0.0300	0.5824
19	-0.0237	0.0131	0.2220	-0.0261	0.0039	0.0759
20	-0.0031	0.0100	0.1697	-0.0002	0.0037	0.0715

Source: Author's computations.

The Dimson model-generated *caar* results in the case of excluded stocks are not any different from those generated under the OLS market model. The results show a decline in the *caar* from 0.55 percent on day -1 to 0.44 percent on the event day (day 0) and a further decline to -0.31 percent on day 1 (a day after the exclusion is effected). Generally, the *caar* results do not exhibit any visible predictable trends in the days after the exclusion takes place. They trend both upwards and downwards although but still their corresponding t-values remain low and hence signalling their statistical insignificancy. What this means is that it is difficult to draw conclusions regarding price reversibility (irreversibility) as implied in the PPH and ISH respectively.

Just like in the case of inclusions, the NSE exclusions depict some price effects on the day before, during and immediately after the event. There is a decline in the *caar* for the stocks deleted from the NSE-20 share index just like it has been discovered to be the case in the developed world, (Shleifer, 1986; and Kaul *et al*., 2000). However the market does not register negative *caar* results on the change date but it is only after day 1 that the *caar* turn out to be negative. However, we need not to overstate this result as it is statistically insignificant.

The findings on index exclusions for this study show more differences than similarities with existing studies' findings. The major difference lies in the statistical insignificance of the results yet almost all earlier studies showed significant results of decreased returns on the day stocks are replaced in an index, (Shleifer, 1986; Harris and Gurel, 1986; Lynch and Mendenhall, 1997; and Shankar and Randhawa, 2006). All these results are based on the US markets apart from the Shankar and Randhawa (2006) ones that compare the price effects in Singapore and Hong Kong markets. In all these cases, the decline in the returns was due to the fact that index funds sought to sell the replaced stocks and in effect their excess supply pushed the prices down.

The index exclusion findings in this study are only found to be similar to those in Shankar and Randhawa (2006) which show that exclusions from the Straits Times Index (STI) of Singapore depict no significant declines in the returns of the affected firms. The absence of index funds and the small number of securities traded is used in explaining such results. The same explanation is applicable to the NSE index exclusion results.

In summary, the stocks deleted from the NSE-20 share index yield reduced returns on the event day and 1 day immediately after the event. However, the observed price effect is not significant because of absence of index funds that sell off the excluded stocks. In addition, since the *caar* results are not significant all through the days after the event it is impossible to determine whether the observed price effects follow the PPH or the ISH.

CHAPTER FIVE

CONCLUSIONS AND IMPLICATIONS

5.1 Introduction

This study's overall objective has been to test behaviour finance theories on a frontier stock exchange such as the NSE. It has tested a single theory from each of the two behavioural finance pillars. These pillars and the tested theories are psychology (overconfidence hypothesis) and the limits-to-arbitrage (index effects).

This chapter concludes the study by providing a summary of the major findings and their implications to policy, practice and behavioural finance theory in general most especially in the context of frontier markets. It ends by pointing out the limitations of the study as well as suggesting areas for further study.

5.2 Conclusions on overconfidence hypothesis

Stock market returns Granger-cause trading volume as predicted by the overconfidence hypothesis. This means that current stock market returns are predictors of future trading activity. Better still, there is a positive and significant cumulative effect of lagged weekly (past stock returns) on trading volume. This is a key result in overconfidence studies that means occurrence of market gains makes the NSE investors to become overconfident and increase their propensity of trading in the hope of ever lasting gains.

Besides, there is no feedback between volume and returns. Specifically, trading volume never Granger-causes stock returns. This result leads to two intuitions; first, since trading volume contains no information to affect returns, the NSE is weak-form efficient; and second sequential information flow and noise trader models are not at play in explaining the overconfidence results in this study. The absence of feedback also means that the study's results are robust.

Overconfidence in its dynamic form is depicted in self-attribution bias. This study finds that the NSE investors trade more when they make right forecasts but their trading reduces slightly when their forecasts are wrong. The psychological bias explaining this result is the self-attribution bias that makes individuals attribute positive results to their foresightedness and negative ones to external forces.

Whereas in developed stock markets the degree of overconfidence depends on the precision of the investors' forecasts, it is not the case in frontier markets like at the NSE. Even when the forecasts of investors are largely imprecise, the level of overconfidence exhibited by the NSE investors is high. This scenario could mean that without fully developed market structures, several investors respond to their whims to trade.

Following the asymmetric ARMA (1, 1)- EGARCH (1, 1) model, it is evident that both the overconfidence-based trading volume and the component that is unrelated to overconfidence affect conditional volatility. However, trading that is unrelated to overconfidence contributes more to conditional volatility than the overconfidence-based trading. Intuitively, overconfidence- based trading as well as other factors contributes to the volatility observed at the NSE.

5.3 Conclusions on index revisions

The event of including of new stocks into the NSE-20 share index produces an increase in the cumulative average abnormal returns on the date of the event. However, this increase is not statistically significant just like in Shankar and Randhawa (2006) who find a similar result in the Singapore market. In contrast to most developed stock markets, inclusion of stocks yields significant abnormal returns on the event day and the days following.

Similarly, the exclusion of old stocks from the NSE-20 share index results into decreased abnormal returns for the affected stocks on the event day; and a further decline that produces negative cumulative average abnormal returns a day after the event. These results on exclusions are not statistically significant just like the inclusion results.

The absence of a significant number of index funds tracking the market index explains the observed insignificant results since the demand and supply conditions for the affected stocks does not change. Besides, the fact that the NSE is a small market with limited securities, it is possible that the investors have sufficient knowledge about the prospects of the majority of the securities in the market. Therefore, index revision announcements and actual changes in such markets do not constitute fundamental news about the affected.

5.4 Implications to Policy and Practice

Since investor behaviour at the NSE conforms to the overconfidence hypothesis and by extension to behavioural finance predictions, it is worthwhile that existing policies and efforts aimed at promoting investor welfare take note of this new development. In other words more effort should be aimed at uncovering the various biases that are inherent in the actions of the investors in order to evaluate the whole set of existing policy positions guiding the interaction of various market players.

Specifically, investor overconfidence breeds excessive trading which causes losses to those who engage in it. But it is known that there are investment advisors and brokers who advise and execute the investors' orders respectively. However, more trading for the investor brings more commissions to the broker and the investment advisor who are acting rationally in maximising their own utility functions at the expense of their client.

Besides, overconfidence causes individuals to inadvertently trade more, hold less diversified portfolios that expose them to high risk. In frontier markets where there are a limited number of securities that one can invest in, investors are limited in their choices. It is therefore recommended that more financial innovations in terms of the products that the NSE provides should be expanded to enable meaningful diversification. It is hoped that when an investor is engaged in excessive trading but they are well diversified their losses could be minimised. In the face of behavioural biases, financial consumer protection should be strengthened. This entails reinforcing financial regulation as well as improving financial literacy hence the study recommends the recasting of the role of the CMA as the regulator of Kenyan capital markets. The CMA has educating and promoting investor awareness as one of its objectives. A meaningful programme of educating investors and promoting awareness should not only concentrate on whether, when and how to invest but also the psychological biases inherent in trading that might cost them resources. It is expected that well informed and psychologically astute investors can better their capital allocation decisions. As suggested in De Meza *et al.,* (2008) and Thaler and Sustein, (2009), financial regulation should incorporate the behavioural biases in various regulations so as to offset their effects in the least intrusive fashion possible.

In Waweru *et al*. (2008), investors both institutional and individual choose their portfolios by studying abnormalities in the trading volume and the market returns as well as tracking the news about the NSE-20 share index. However, the practice of using volume in order for one to invest shows that it may not be appropriate because causality moves from market returns to volume and not in the opposite direction. Hence investors who choose their portfolios by observing volume may not generate profits.

Index revisions of the NSE contain no information regarding the future profitability or unprofitability of the affected stocks. This implies that investment strategies attempting to profit from index revisions by buying stocks included into the NSE-20 share index and selling those excluded do not yield significant capital gains. The fact that there are no significant abnormal returns following revisions also implies that in practice investors at the NSE easily and quickly get news regarding the market index most of the times.

5.5 Implications to behavioural finance theory

The findings of this study as far as behavioural finance theories are concerned indicate that human information processing biases are inherent in frontier markets. The two pillars of behavioural finance that is psychology and the limits-to-arbitrage are capable of explaining various phenomena at the NSE. Generally, the basic predictions of the overconfidence bias and the index revision hold.

The overconfidence bias predicts that current market gains increase future trading activity whereas increased trading activity never increases market returns. Besides, investors increase their trading when they find out that their forecasts of the market returns are accurate but they never reduce trading when they make wrong forecasts. Hence the theory of overconfidence and biased self-attribution hold in the NSE.

Further the overconfidence theory also asserts that as investor forecasts of the future market returns move closer to the actual returns in the market, the investors increase their trading; this is the case in developed markets. However, trading in frontier markets (the NSE) shows that even when the forecasts are highly imprecise investors still depict high levels of overconfidence as they engage in more trading.

In addition, overconfidence theory predicts that overconfidence-based trading contributes to excess volatility in markets. Specifically, a comparison of overconfidence-based trading volume with trading that is unrelated to overconfidence shows that the former results in higher volatility in the market than the latter. However this study shows that much as overconfidence-based trading results in high volatility, it is trading that is unrelated to overconfidence that leads to higher volatility at the NSE.

In testing the index revision theories that predict positive (negative) abnormal returns when stocks are added to or removed from the market index, the study yields statistically insignificant results. Much as there are abnormal returns following the revisions they are insignificant. Such a result is explained by the fact that the NSE does not have many index funds tracking the index, and in addition, the market has fewer securities in that revisions are not viewed as carrying fundamental news relating to the affected securities.

Overall, the predictions of behavioural finance theories that were developed in the context of developed markets can be used in explaining market phenomena in frontier markets. There are traceable biases in the volume and returns variables that are explainable through psychology. Also, the use of index revisions is one example that can illuminate the limits-to- arbitrage argument most especially if a market is highly liquid. The fact that this study yielded statistically insignificant results is perhaps attributed to the small size of the NSE and therefore fewer securities.

5.6 Limitations of the study and suggested further works

The relatively small number of stocks considered in studying the two objectives of overconfidence bias and index revisions is likely to affect this study's conclusions. Specifically only 9 out of the 20 securities constituting the NSE-20 share index were considered in the overconfidence analysis. This was due to incomplete data for some securities. Similarly, the index revisions of the NSE-20 share index yield fewer events which constrain our analysis.

One area that needs further investigation is the analysis of the various categories of investors to attempt to establish the variations in the overconfidence levels exhibited. This would help give a micro dimension to this work that has basically considered overconfidence at the macro level.

There other psychological biases that need to be studied in order to establish how other market players such as investment advisors and stock brokers perform in their professions. The question would be to find out if there are inherent psychological biases affecting their decisions or they act rationally. This would help in tailoring regulation that is behavioural finance-biased so as to improve market outcomes.

In index changes we are unable to find significant price movements in the affected securities. One could consider examining the trading volumes of the affected securities whether they exhibit any abnormality or not. Such a study would perhaps help in showing whether the insignificant abnormal returns also coincide with insignificant volume or not.

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APPENDIX

Appendix Table 1.1: Quality of Markets Criteria

CRITERIA	Developed	Adv Emerging	Sec Emerging	Frontier
Market and Regulatory Environment				
Formal Stock Market regulatory authorities actively monitor market	x	x	x	x
Fair and non-prejudicial treatment of minority share holders	x	x		
Non or selective incidence of foreign ownership restrictions	x	x		
No objections or significant restrictions or penalties applied on the repatriation of capital	x	x	x	x
Free and well-developed equity market	x	x		
Free and well-developed foreign exchange market	x	x		
Non or simple registration process for foreign investors	x	x		
Custody and Settlement				
Settlement-Rare incidence of failed trades	x	x	x	x
Custody- Sufficient competition to ensure high quality custodian services	x	x	x	
Clearing and Settlement- T+3 or shorter, T+7 or shorter for frontier	x	x	x	x
Stock Lending is permitted	x			
Settlement-Free delivery available	x			
Custody- Omnibus account facilities available to international investors	x	x		
Dealing Landscape				
Brokerage- Sufficient competition to ensure high quality broker services	x	x	x	
Liquidity- Sufficient broad market liquidity to support sizeable global investment	x	x	x	
Transaction costs- implicit and explicit costs to be reasonable and competitive	x	x	x	
Short sales permitted	x			
Off-exchange transactions permitted	x			
Efficient trading mechanism	x			
Transparency-market depth information/visibility and timely trade reporting process	x	x	x	x
Derivatives				
Developed derivatives Market	x			

Source: FTSE (2010)

Appendix Table 1.2: The NSE-listed companies as at December 31, 2010

(i)	**MAIN INVESTMENT MARKET SEGMENT(MIMS)**
(a)	**AGRICULTURAL**
1	Kakuzi
2	Rea Vipingo Plantations Ltd
3	Sasini Ltd
(b)	**COMMERCIAL AND SERVICES**
4	AccessKenya Group Ltd
5	Car & General (K) Ltd
6	CMC Holdings Ltd
7	Hutchings Biemer Ltd
8	Kenya Airways Ltd
9	Marshalls (E.A.) Ltd
10	Nation Media Group
11	Safaricom limited
12	Scangroup Ltd
13	Standard Group Ltd
14	TPS Eastern Africa (Serena) Ltd
15	Uchumi Supermarket Ltd
(c)	**FINANCE AND INVESTMENT**
16	Barclays Bank Ltd
17	Centum Investment Company Ltd
18	CFC Stanbic Holdings Ltd
19	Diamond Trust Bank Kenya Ltd
20	Equity Bank Ltd
21	Housing Finance Co Ltd
22	Jubilee Holdings Ltd
23	Kenya Commercial Bank Ltd
24	Kenya Re-Insurance Corporation Ltd
25	National Bank of Kenya Ltd
26	NIC Bank Ltd
27	Olympia Capital Holdings ltd
28	Pan Africa Insurance Holdings Ltd
29	Standard Chartered Bank Ltd
30	The Co-operative Bank of Kenya Ltd
(d)	**INDUSTRIAL AND ALLIED**
31	Athi River Mining
32	B.O.C Kenya Ltd
33	Bamburi Cement Ltd

34	British American Tobacco Kenya Ltd
35	Carbacid Investments Ltd
36	Crown Berger Ltd
37	E.A.Cables Ltd
38	E.A.Portland Cement Ltd
39	East African Breweries Ltd
40	Eveready East Africa Ltd
41	KenolKobil Ltd
42	Kenya Power & Lighting Ltd
43	KenGen Ltd.
44	Mumias Sugar Co. Ltd
45	Sameer Africa Ltd
46	Total Kenya Ltd
47	Unga Group Ltd
(ii)	**ALTERNATIVE INVESTMENT MARKET SEGMENT (AIMS)**
48	A.Baumann & Co.Ltd
49	City Trust Ltd
50	Eaagads Ltd
51	Express Ltd
52	Williamson Tea Kenya Ltd
53	Kapchorua Tea Co. Ltd
54	Kenya Orchards Ltd
55	Limuru Tea Co. Ltd

Source: NSE Price List December 31, 2010.

Appendix Table 1.3: Quality of Markets Criteria (African Countries' Performance)

CRITERIA	De v	Adv Em g	*South Africa*	Sec Em g	*Egypt*	*Morocco*
World Bank GNI percapita Rating, 2010			UpperMiddle		Lower Middle	Lower Middle
Market and Regulatory Environment						
Formal Stock Market regulatory authorities actively monitor market	x	x	Pass	x	Pass	Pass
Fair and non-prejudicial treatment of minority share holders	x	x	Pass		Pass	Pass
Non or selective incidence of foreign ownership restrictions	x	x	Pass		Pass	Pass
No objections or significant restrictions or penalties applied on the repatriation of capital	x	x	Pass	x	Pass	Pass
Free and well-developed equity market	x	x	Pass		Pass	Unmet
Free and well-developed foreign exchange market	x	x	Pass		Unmet	Unmet
Non or simple registration process for foreign investors	x	x	Pass		Pass	Pass
Custody and Settlement						
Settlement-Rare incidence of failed trades	x	x	Pass	x	Pass	Pass
Custody- Sufficient competition to ensure high quality custodian services	x	x	Pass	x	Pass	Pass
Clearing and Settlement- T+3 or shorter, T+7 or shorter for frontier	x	x	T+5	x	T+3	T+3
Stock Lending is permitted	x		Pass		Restricted	Pass
Settlement-Free delivery available	x		Pass		Pass	Unmet
Custody- Omnibus account facilities available to international investors	x	x	Pass		Restricted	Restricted
Dealing Landscape						
Brokerage- Sufficient competition to ensure high quality broker services	x	x	Pass	x	Pass	Pass
Liquidity- Sufficient broad market liquidity to support sizeable global investment	x	x	Pass	x	Pass	Unmet
Transaction costs- implicit and explicit costs to be reasonable and competitive	x	x	Pass	x	Pass	Pass
Short sales permitted	x		Pass		Unmet	Unmet
Off-exchange transactions permitted	x		Pass		Unmet	Unmet
Efficient trading mechanism	x		Pass		Pass	Pass

Transparency-market depth information/visibility and timely trade reporting process	x	x	Pass	x	Pass	Pass
Derivatives						
Developed derivatives Market	x		Pass		Unmet	Unmet
Size of the Market						
Market Capitalisation $US Millions (as at December 31, 2010)			925,007		84,277	69,390
Total Number of Listed Companies (as at December 31, 2010)			352		227	74

Source: FTSE (2010).

Appendix Table 1.3 Continued.

CRITERIA	**Dev**	**Frontier**	***Botswana***	***Ivory Coast***	***Kenya***	***Mauritius***	***Nigeria***	***Tunisia***	***Ghana***
World Bank GNI percapita Rating, 2010			Upper Middle	Lower Middle	**Low**	Upper Middle	Lower Middle	Upper Middle	Lower Middle
Market and Regulatory Environment									
Formal Stock Market regulatory authorities actively monitor market	x	x	Restrict	Pass	**Pass**	Pass	Pass	Pass	Pass
Fair and non-prejudicial treatment of minority share holders	x		Restrict	Restrict	**Restrict**	Restrict	Restrict	Restrict	Restrict
Non or selective incidence of foreign ownership restrictions	x		Restrict	Pass	**Restrict**	Pass	Pass	Restrict	Restrict
No objections or significant restrictions or penalties applied on the repatriation of capital	x	x	Pass	Restrict	**Pass**	Pass	Pass	Pass	Pass
Free and well-developed equity market	x		Unmet	Unmet	**Unmet**	Unmet	Restrict	Unmet	Restrict
Free and well-developed foreign exchange market	x		Umet	Unmet	**Unmet**	Unmet	Unmet	Unmet	Unmet
Non or simple registration process for foreign investors	x		Restrict	Restrict	**Restrict**	Restrict	Restrict	Restrict	Restrict
Custody and Settlement									
Settlement-Rare incidence of failed trades	x	x	Pass	Pass	**Pass**	Pass	Pass	Pass	Pass
Custody- Sufficient competition to ensure high quality custodian services	x		Pass	Pass	**Pass**	Pass	Pass	Pass	Restrict
Clearing and Settlement- T+3 or shorter, T+7 or shorter for frontier	x	x	T+4	T+5	**T+4**	T+5	T+3	T+3	T+3
Stock Lending is permitted	x		Unmet	Unmet	**Unmet**	Restrict	Unmet	Unmet	Unmet
Settlement-Free delivery available	x		Unmet	Unmet	**Unmet**	Pass	Unmet	Unmet	Unmet
Custody- Omnibus account facilities available to international investors	x		Unmet	Unmet	**Unmet**	Unmet	Unmet	Unmet	Unmet
Dealing Landscape									
Brokerage- Sufficient competition to ensure high quality broker services	x		Pass	Pass	**Pass**	Pass	Pass	Pass	Pass

Liquidity- Sufficient broad market liquidity to support sizeable global investment	x		Unmet	Unmet	**Unmet**	Unmet	Restrict	Un Met	Unmet
Transaction costs- implicit and explicit costs to be reasonable and competitive	x		Pass	Restrict	**Pass**	Pass	Pass	Pass	Restrict
Short sales permitted	x		Unmet	Unmet	**Unmet**	Unmet	Unmet	Unmet	Unmet
Off-exchange transactions permitted	x		Unmet	Unmet	**Restrict**	Unmet	Restrict	Unmet	Restrict
Efficient trading mechanism	x		Restrict	Restrict	**Restrict**	Restrict	Restrict	Restrict	Restrict
Transparency-market depth information/visibility and timely trade reporting process	x	x	Pass	Pass	**Pass**	Pass	Pass	Pass	Pass
Derivatives									
Developed derivatives Market	x		Unmet	Unmet	**Unmet**	Unmet	Unmet	Unmet	Unmet
Size of the Market									
Market Capitalisation $US Millions (as at December 31, 2010)			4,076	1,185	**14,461**	7,753	56,579	10,682	2,470
Total Number of Listed Companies (as at December 31, 2010)			20	33	**55**	62	217	56	20

Source : FTSE (2010)

Appendix Table 1.4: Correlograms of the NSE-20 share weekly returns r_t .

Date: 11/18/11 Time: 13:55
Sample: 1/18/2001 8/26/2010
Included observations: 502

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.063</td><td>0.063</td><td>2.0262</td><td>0.155</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.047</td><td>0.043</td><td>3.1252</td><td>0.210</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>3</td><td>0.087</td><td>0.082</td><td>6.9358</td><td>0.074</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>4</td><td>-0.058</td><td>-0.071</td><td>8.6611</td><td>0.070</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.015</td><td>0.016</td><td>8.7782</td><td>0.118</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>6</td><td>0.131</td><td>0.130</td><td>17.527</td><td>0.008</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.000</td><td>-0.006</td><td>17.527</td><td>0.014</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.015</td><td>-0.003</td><td>17.645</td><td>0.024</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.048</td><td>0.029</td><td>18.803</td><td>0.027</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.023</td><td>-0.011</td><td>19.072</td><td>0.039</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.034</td><td>0.029</td><td>19.671</td><td>0.050</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>12</td><td>0.108</td><td>0.087</td><td>25.694</td><td>0.012</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.023</td><td>0.017</td><td>25.969</td><td>0.017</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>0.009</td><td>-0.013</td><td>26.008</td><td>0.026</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.040</td><td>0.021</td><td>26.859</td><td>0.030</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.056</td><td>0.070</td><td>28.485</td><td>0.028</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>0.020</td><td>0.003</td><td>28.694</td><td>0.037</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>0.067</td><td>0.032</td><td>31.049</td><td>0.028</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>0.031</td><td>0.017</td><td>31.543</td><td>0.035</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>0.002</td><td>-0.002</td><td>31.545</td><td>0.048</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>0.038</td><td>0.018</td><td>32.300</td><td>0.055</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.024</td><td>0.014</td><td>32.600</td><td>0.068</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>-0.047</td><td>-0.058</td><td>33.767</td><td>0.069</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>0.015</td><td>-0.010</td><td>33.883</td><td>0.087</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>0.049</td><td>0.048</td><td>35.181</td><td>0.085</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>26</td><td>0.032</td><td>0.039</td><td>35.712</td><td>0.097</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>27</td><td>0.018</td><td>-0.017</td><td>35.887</td><td>0.118</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>28</td><td>0.019</td><td>-0.007</td><td>36.073</td><td>0.141</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>29</td><td>0.056</td><td>0.069</td><td>37.754</td><td>0.128</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>0.005</td><td>-0.012</td><td>37.770</td><td>0.156</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>31</td><td>-0.025</td><td>-0.053</td><td>38.094</td><td>0.178</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>32</td><td>0.070</td><td>0.063</td><td>40.698</td><td>0.139</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>33</td><td>-0.064</td><td>-0.076</td><td>42.906</td><td>0.116</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>34</td><td>-0.037</td><td>-0.049</td><td>43.656</td><td>0.124</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>35</td><td>0.052</td><td>0.050</td><td>45.119</td><td>0.118</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>36</td><td>-0.068</td><td>-0.055</td><td>47.633</td><td>0.093</td></tr>
</table>

Appendix Table 1.5: Correlograms of the NSE-20 share squared return series.

Date: 11/18/11 Time: 14:17
Sample: 1/18/2001 8/26/2010
Included observations: 502

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.219	0.219	24.158	0.000
.|* |	.|* |	2	0.130	0.087	32.754	0.000
.|* |	.|. |	3	0.087	0.045	36.598	0.000
.|* |	.|* |	4	0.111	0.079	42.909	0.000
.|. |	.|. |	5	0.015	-0.036	43.028	0.000
.|. |	.|. |	6	0.043	0.028	43.979	0.000
.|. |	.|. |	7	0.063	0.045	45.987	0.000
.|. |	.|. |	8	0.038	0.005	46.740	0.000
.|. |	.|. |	9	0.022	0.004	46.989	0.000
.|. |	.|. |	10	0.004	-0.016	46.998	0.000
.|. |	.|. |	11	0.018	0.009	47.167	0.000
.|. |	.|. |	12	-0.015	-0.024	47.282	0.000
.|* |	.|* |	13	0.100	0.109	52.417	0.000
.|. |	.|. |	14	-0.009	-0.052	52.459	0.000
.|. |	.|. |	15	0.027	0.019	52.830	0.000
.|. |	.|. |	16	0.056	0.051	54.463	0.000
.|* |	.|* |	17	0.117	0.083	61.656	0.000
.|. |	.|. |	18	0.020	-0.021	61.874	0.000
.|. |	.|. |	19	0.069	0.045	64.399	0.000
.|. |	.|. |	20	0.033	-0.013	64.984	0.000
.|. |	.|. |	21	0.039	0.011	65.788	0.000
.|. |	.|. |	22	0.013	-0.002	65.881	0.000
.|. |	.|. |	23	0.017	-0.004	66.040	0.000
.|. |	.|. |	24	0.003	-0.018	66.044	0.000
.|. |	.|. |	25	0.006	0.007	66.065	0.000
.|. |	.|. |	26	-0.000	-0.020	66.065	0.000
.|. |	.|. |	27	0.011	0.022	66.130	0.000
.|. |	.|. |	28	-0.016	-0.026	66.264	0.000
.|. |	.|. |	29	0.001	0.006	66.264	0.000
.|. |	.|. |	30	-0.010	-0.028	66.320	0.000
.|. |	.|. |	31	-0.011	0.008	66.390	0.000
.|. |	.|. |	32	0.035	0.031	67.037	0.000
.|. |	.|. |	33	0.013	-0.002	67.131	0.000
.|. |	.|. |	34	0.030	0.014	67.629	0.001
.|* |	.|* |	35	0.091	0.087	72.081	0.000
.|. |	*|. |	36	-0.005	-0.067	72.094	0.000

Appendix Table 1.6: SUR results for returns and equal-weighted volume

Estimation Method: Seemingly Unrelated Regression
Date: 10/30/11 Time: 19:01
Sample: 2/15/2001 8/26/2010
Included observations: 498
Total system (balanced) observations 996
Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.066577	0.046589	1.429046	0.1533
C(2)	0.062870	0.047394	1.326551	0.1850
C(3)	0.101275	0.047339	2.139371	0.0327
C(4)	-0.084327	0.047038	-1.792749	0.0733
C(5)	-0.521119	1.666003	-0.312796	0.7545
C(6)	-2.104046	1.754970	-1.198907	0.2309
C(7)	0.587691	1.754309	0.334998	0.7377
C(8)	2.210410	1.606645	1.375793	0.1692
C(9)	0.146848	0.140189	1.047504	0.2951
C(10)	0.006009	0.001279	4.699644	0.0000
C(11)	0.001627	0.001301	1.250484	0.2114
C(12)	0.001743	0.001299	1.341791	0.1800
C(13)	-0.000994	0.001291	-0.769671	0.4417
C(14)	0.319502	0.045727	6.987210	0.0000
C(15)	0.087202	0.048168	1.810352	0.0705
C(16)	3.91E-05	0.048150	0.000811	0.9994
C(17)	0.211822	0.044097	4.803503	0.0000
C(18)	-0.001378	0.003848	-0.358177	0.7203
Determinant residual covariance		0.064706		

Equation: RT = C(1)*RT(-1) + C(2)*RT(-2) + C(3)*RT(-3) + C(4)*RT(
-4) + C(5)*DEWV(-1) + C(6)*DEWV(-2) + C(7)*DEWV(-3) +
C(8)*DEWV(-4) + C(9)
Observations: 498

R-squared	0.024311	Mean dependent var	0.172808
Adjusted R-squared	0.008349	S.D. dependent var	3.149153
S.E. of regression	3.135979	Sum squared resid	4809.004
Durbin-Watson stat	2.003149		

Equation: DEWV = C(10)*RT(-1) + C(11)*RT(-2) + C(12)*RT(-3) +
C(13)*RT(-4) + C(14)*DEWV(-1) + C(15)*DEWV(-2) + C(16)
*DEWV(-3) + C(17)*DEWV(-4) + C(18)
Observations: 498

R-squared	0.314071	Mean dependent var	-0.000128
Adjusted R-squared	0.302849	S.D. dependent var	0.103087
S.E. of regression	0.086073	Sum squared resid	3.622781
Durbin-Watson stat	2.015940		

Appendix Table 1.7: SUR results for returns and value-weighted volume

Estimation Method: Seemingly Unrelated Regression
Date: 10/30/11 Time: 22:05
Sample: 2/01/2001 8/26/2010
Included observations: 500
Total system (balanced) observations 1000
Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.063460	0.045765	1.386656	0.1659
C(2)	0.047670	0.046121	1.033592	0.3016
C(3)	-1.040045	3.528519	-0.294754	0.7682
C(4)	-0.614366	3.447355	-0.178214	0.8586
C(5)	0.154207	0.140446	1.097985	0.2725
C(6)	0.002155	0.000588	3.663177	0.0003
C(7)	0.000605	0.000593	1.020844	0.3076
C(8)	0.320818	0.045359	7.072866	0.0000
C(9)	0.121868	0.044316	2.749993	0.0061
C(10)	-0.000533	0.001805	-0.294969	0.7681
Determinant residual covariance		0.015130		

Equation: RT = C(1)*RT(-1) + C(2)*RT(-2) + C(3)*DVWV(-1) + C(4)
*DVWV(-2) + C(5)
Observations: 500

R-squared	0.006212	Mean dependent var	0.174092
Adjusted R-squared	-0.001819	S.D. dependent var	3.142917
S.E. of regression	3.145773	Sum squared resid	4898.465
Durbin-Watson stat	2.006839		

Equation: DVWV = C(6)*RT(-1) + C(7)*RT(-2) + C(8)*DVWV(-1) +
C(9)*DVWV(-2) + C(10)
Observations: 500

R-squared	0.202796	Mean dependent var	-9.80E-05
Adjusted R-squared	0.196354	S.D. dependent var	0.045109
S.E. of regression	0.040439	Sum squared resid	0.809471
Durbin-Watson stat	2.015539		

Appendix Table 1.8: Correlograms of residuals of Returns (residrtns) corresponding to detrended value-weighted volume

Sample: 1/18/2001 8/26/2010
Included observations: 500

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.004	-0.004	0.0077	0.930
.|. |	.|. |	2	-0.002	-0.002	0.0098	0.995
.|* |	.|* |	3	0.089	0.089	4.0267	0.259
*|. |	*|. |	4	-0.070	-0.070	6.5402	0.162
.|. |	.|. |	5	0.009	0.009	6.5806	0.254
.|* |	.|* |	6	0.136	0.130	16.015	0.014
.|. |	.|. |	7	-0.009	0.003	16.058	0.025
.|. |	.|. |	8	0.009	0.002	16.100	0.041
.|. |	.|. |	9	0.048	0.028	17.292	0.044
.|. |	.|. |	10	-0.031	-0.013	17.800	0.058
.|. |	.|. |	11	0.029	0.025	18.220	0.077
.|* |	.|* |	12	0.107	0.088	24.152	0.019
.|. |	.|. |	13	0.015	0.025	24.275	0.029
.|. |	.|. |	14	0.001	-0.009	24.276	0.042
.|. |	.|. |	15	0.038	0.019	25.023	0.050
.|. |	.|. |	16	0.051	0.069	26.359	0.049
.|. |	.|. |	17	0.011	0.005	26.416	0.067
.|. |	.|. |	18	0.065	0.036	28.595	0.054
.|. |	.|. |	19	0.027	0.021	28.988	0.066
.|. |	.|. |	20	-0.004	-0.000	28.999	0.088
.|. |	.|. |	21	0.039	0.021	29.800	0.096
.|. |	.|. |	22	0.026	0.020	30.160	0.115
.|. |	.|. |	23	-0.051	-0.056	31.516	0.111
.|. |	.|. |	24	0.014	-0.017	31.626	0.137
.|. |	.|. |	25	0.048	0.041	32.846	0.135
.|. |	.|. |	26	0.027	0.041	33.219	0.156
.|. |	.|. |	27	0.012	-0.015	33.297	0.187
.|. |	.|. |	28	0.013	-0.010	33.393	0.222
.|. |	.|. |	29	0.056	0.069	35.070	0.202
.|. |	.|. |	30	0.001	-0.008	35.070	0.240
.|. |	.|. |	31	-0.028	-0.051	35.486	0.265
.|* |	.|. |	32	0.078	0.066	38.747	0.191
*|. |	*|. |	33	-0.067	-0.074	41.161	0.156
.|. |	.|. |	34	-0.037	-0.052	41.889	0.166
.|. |	.|. |	35	0.059	0.043	43.784	0.147
*|. |	.|. |	36	-0.079	-0.062	47.119	0.102

Appendix Table 1.9: Correlograms of residuals from detrended value-weighted volume (residdvwv)

Sample: 1/18/2001 8/26/2010
Included observations: 500

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.008	-0.008	0.0308	0.861
.|. |	.|. |	2	-0.036	-0.036	0.6971	0.706
.|. |	.|. |	3	0.003	0.003	0.7019	0.873
.|. |	.|. |	4	0.073	0.071	3.3666	0.498
.|. |	.|. |	5	0.030	0.031	3.8101	0.577
.|. |	.|. |	6	0.067	0.073	6.1040	0.412
.|. |	.|. |	7	0.045	0.049	7.1570	0.413
.|* |	.|* |	8	0.120	0.123	14.496	0.070
.|. |	.|. |	9	0.001	0.005	14.497	0.106
.|. |	.|. |	10	0.018	0.018	14.656	0.145
.|. |	.|. |	11	0.041	0.032	15.512	0.160
.|. |	.|. |	12	-0.014	-0.037	15.612	0.210
.|. |	.|. |	13	0.066	0.056	17.889	0.162
.|. |	.|. |	14	0.010	-0.012	17.944	0.209
.|. |	.|. |	15	0.068	0.058	20.337	0.159
.|* |	.|. |	16	0.075	0.064	23.237	0.108
.|. |	.|. |	17	0.073	0.071	25.969	0.075
.|. |	.|. |	18	0.018	0.024	26.144	0.097
.|. |	.|. |	19	-0.025	-0.040	26.460	0.118
.|. |	.|. |	20	0.030	0.021	26.942	0.137
.|. |	.|. |	21	0.066	0.027	29.217	0.109
.|. |	.|. |	22	-0.015	-0.034	29.342	0.135
.|. |	.|. |	23	-0.030	-0.056	29.812	0.155
.|. |	.|. |	24	0.033	-0.002	30.392	0.172
.|. |	.|. |	25	0.055	0.035	31.990	0.158
.|. |	.|. |	26	0.048	0.040	33.213	0.156
.|. |	.|. |	27	-0.049	-0.041	34.511	0.152
.|* |	.|* |	28	0.082	0.074	38.104	0.096
*|. |	*|. |	29	-0.095	-0.116	42.930	0.046
.|. |	*|. |	30	-0.059	-0.072	44.797	0.040
.|. |	.|. |	31	0.070	0.049	47.392	0.030
.|. |	.|. |	32	0.071	0.034	50.084	0.022
*|. |	*|. |	33	-0.071	-0.077	52.802	0.016
.|. |	.|. |	34	0.055	0.051	54.424	0.015
.|. |	.|. |	35	-0.048	-0.040	55.644	0.015
.|. |	.|. |	36	-0.016	-0.030	55.788	0.019

Appendix Table 1.10: Correlograms for residuals of returns (residrtns) corresponding to the detrended equal-weighted volume

Sample: 1/18/2001 8/26/2010

Included observations: 498

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.002	-0.002	0.0027	0.959
.|. |	.|. |	2	0.006	0.006	0.0207	0.990
.|. |	.|. |	3	-0.015	-0.015	0.1367	0.987
.|. |	.|. |	4	-0.008	-0.008	0.1695	0.997
.|. |	.|. |	5	0.000	0.000	0.1695	0.999
.|* |	.|* |	6	0.123	0.123	7.7981	0.253
.|. |	.|. |	7	0.005	0.005	7.8085	0.350
.|. |	.|. |	8	0.001	-0.001	7.8089	0.452
.|. |	.|. |	9	0.021	0.024	8.0255	0.532
.|. |	.|. |	10	-0.027	-0.025	8.4092	0.589
.|. |	.|. |	11	0.023	0.022	8.6700	0.652
.|* |	.|* |	12	0.103	0.090	14.062	0.297
.|. |	.|. |	13	0.015	0.014	14.181	0.361
.|. |	.|. |	14	0.003	0.002	14.187	0.436
.|. |	.|. |	15	0.023	0.022	14.465	0.491
.|. |	.|. |	16	0.047	0.057	15.629	0.479
.|. |	.|. |	17	0.015	0.011	15.738	0.542
.|. |	.|. |	18	0.060	0.038	17.584	0.483
.|. |	.|. |	19	0.021	0.021	17.803	0.536
.|. |	.|. |	20	0.009	0.008	17.843	0.598
.|. |	.|. |	21	0.029	0.024	18.292	0.630
.|. |	.|. |	22	0.022	0.017	18.537	0.674
.|. |	.|. |	23	-0.049	-0.057	19.813	0.653
.|. |	.|. |	24	0.003	-0.019	19.818	0.707
.|. |	.|. |	25	0.041	0.035	20.684	0.710
.|. |	.|. |	26	0.026	0.025	21.038	0.740
.|. |	.|. |	27	0.003	-0.013	21.043	0.784
.|. |	.|. |	28	0.016	0.003	21.179	0.818
.|. |	.|. |	29	0.043	0.054	22.178	0.813
.|. |	.|. |	30	0.002	-0.007	22.180	0.847
.|. |	.|. |	31	-0.023	-0.040	22.471	0.868
.|. |	.|. |	32	0.060	0.055	24.396	0.830
.|. |	*|. |	33	-0.056	-0.069	26.088	0.798
.|. |	.|. |	34	-0.032	-0.049	26.633	0.812
.|. |	.|. |	35	0.043	0.045	27.623	0.808
*|. |	*|. |	36	-0.072	-0.078	30.438	0.730

Appendix Table 1.11: Correlograms of residuals from detrended equal-weighted volume (residewt)
Sample: 1/18/2001 8/26/2010
Included observations: 498

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.008	-0.008	0.0350	0.852
.|. |	.|. |	2	-0.010	-0.010	0.0844	0.959
.|. |	.|. |	3	-0.004	-0.005	0.0946	0.992
.|. |	.|. |	4	-0.025	-0.025	0.4000	0.982
.|. |	.|. |	5	0.017	0.016	0.5384	0.991
.|. |	.|. |	6	0.027	0.027	0.9089	0.989
.|. |	.|. |	7	-0.014	-0.014	1.0091	0.995
.|. |	.|. |	8	0.020	0.020	1.2063	0.997
.|. |	.|. |	9	-0.033	-0.032	1.7506	0.995
.|. |	.|. |	10	0.008	0.009	1.7851	0.998
.|. |	.|. |	11	-0.024	-0.026	2.0873	0.998
*|. |	*|. |	12	-0.072	-0.072	4.7406	0.966
.|* |	.|* |	13	0.085	0.083	8.4369	0.814
.|. |	.|. |	14	0.057	0.058	10.132	0.752
.|. |	.|. |	15	0.037	0.040	10.853	0.763
.|. |	.|. |	16	-0.022	-0.025	11.110	0.803
.|. |	.|. |	17	0.053	0.063	12.547	0.766
.|. |	.|. |	18	-0.008	-0.006	12.584	0.816
.|. |	.|. |	19	-0.056	-0.063	14.238	0.770
.|. |	.|. |	20	0.050	0.049	15.550	0.744
.|. |	.|. |	21	0.065	0.062	17.722	0.666
.|. |	.|. |	22	-0.039	-0.035	18.516	0.675
.|. |	*|. |	23	-0.055	-0.066	20.090	0.636
.|. |	.|. |	24	0.018	0.028	20.263	0.682
.|. |	.|. |	25	0.010	0.027	20.318	0.730
.|. |	.|. |	26	0.004	-0.000	20.325	0.776
.|. |	.|. |	27	0.032	0.024	20.861	0.793
.|* |	.|* |	28	0.097	0.096	25.805	0.584
*|. |	.|. |	29	-0.069	-0.060	28.368	0.498
.|. |	.|. |	30	-0.040	-0.059	29.203	0.507
.|. |	.|. |	31	0.045	0.041	30.302	0.502
.|. |	.|. |	32	0.012	0.033	30.379	0.549
.|. |	.|. |	33	-0.043	-0.049	31.365	0.549
.|. |	.|. |	34	0.008	-0.023	31.398	0.596
.|. |	.|. |	35	0.007	0.013	31.426	0.641
.|. |	.|. |	36	0.007	0.027	31.451	0.685

Appendix Table 1.12: Output of the mean equation used to establish ARCH effect.

Dependent Variable: RT
Method: Least Squares
Included observations: 501 after adjustments
Convergence achieved after 11 iterations
MA Backcast: 1/18/2001

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.254724	0.277541	0.917786	0.3592
AR(1)	0.967293	0.030218	32.01041	0.0000
MA(1)	-0.938500	0.040930	-22.92961	0.0000

R-squared	0.016204	Mean dependent var	0.173601
Adjusted R-squared	0.012253	S.D. dependent var	3.139791
S.E. of regression	3.120496	Akaike info criterion	5.119831
Sum squared resid	4849.273	Schwarz criterion	5.145080
Log likelihood	-1279.518	Hannan-Quinn criter.	5.129738
F-statistic	4.101283	Durbin-Watson stat	1.958613
Prob(F-statistic)	0.017114		

Inverted AR Roots	.97
Inverted MA Roots	.94

Appendix Table 1.13: Correlograms of Squared residuals from the mean equation

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.194	0.194	18.901	
.|* |	.|* |	2	0.113	0.078	25.319	
.|. |	.|. |	3	0.072	0.039	27.957	0.000
.|* |	.|* |	4	0.104	0.080	33.479	0.000
.|. |	.|. |	5	0.018	-0.024	33.644	0.000
.|. |	.|. |	6	0.056	0.041	35.232	0.000
.|. |	.|. |	7	0.065	0.044	37.397	0.000
.|. |	.|. |	8	0.040	0.007	38.209	0.000
.|. |	.|. |	9	0.013	-0.006	38.298	0.000
.|. |	.|. |	10	0.003	-0.014	38.302	0.000
.|. |	.|. |	11	0.018	0.011	38.474	0.000
.|. |	.|. |	12	-0.016	-0.025	38.605	0.000
.|* |	.|* |	13	0.099	0.106	43.624	0.000
.|. |	.|. |	14	-0.013	-0.052	43.711	0.000
.|. |	.|. |	15	0.015	0.008	43.832	0.000
.|. |	.|. |	16	0.042	0.043	44.745	0.000
.|* |	.|. |	17	0.086	0.058	48.599	0.000
.|. |	.|. |	18	0.023	0.000	48.871	0.000
.|* |	.|. |	19	0.090	0.070	53.122	0.000
.|. |	.|. |	20	0.028	-0.020	53.538	0.000
.|. |	.|. |	21	0.042	0.017	54.474	0.000
.|. |	.|. |	22	0.014	-0.003	54.578	0.000
.|. |	.|. |	23	0.021	-0.004	54.813	0.000
.|. |	.|. |	24	0.005	-0.012	54.826	0.000
.|. |	.|. |	25	0.015	0.010	54.945	0.000
.|. |	.|. |	26	0.002	-0.023	54.946	0.000
.|. |	.|. |	27	0.015	0.021	55.067	0.000
.|. |	.|. |	28	-0.013	-0.021	55.156	0.001
.|. |	.|. |	29	-0.003	-0.004	55.162	0.001
.|. |	.|. |	30	-0.006	-0.015	55.180	0.002
.|. |	.|. |	31	-0.008	0.005	55.217	0.002
.|. |	.|. |	32	0.040	0.031	56.073	0.003
.|. |	.|. |	33	0.010	0.001	56.124	0.004
.|. |	.|. |	34	0.032	0.019	56.684	0.005
.|* |	.|* |	35	0.097	0.090	61.740	0.002
.|. |	.|. |	36	-0.003	-0.061	61.745	0.002

Appendix Table 1.14: Correlograms of standardised residuals of the estimated mean equation of the ARMA (1, 1) - GARCH (1, 1).

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.013	0.013	0.0800	
.|. |	.|. |	2	-0.042	-0.042	0.9807	
.|. |	.|. |	3	-0.031	-0.030	1.4786	0.224
*|. |	*|. |	4	-0.076	-0.078	4.4424	0.108
.|. |	.|. |	5	-0.032	-0.034	4.9751	0.174
.|* |	.|. |	6	0.079	0.073	8.1462	0.086
.|. |	.|. |	7	-0.006	-0.015	8.1661	0.147
.|. |	.|. |	8	-0.050	-0.051	9.4197	0.151
.|. |	.|. |	9	0.018	0.018	9.5870	0.213
.|. |	.|. |	10	-0.036	-0.032	10.263	0.247
.|. |	.|. |	11	-0.004	-0.002	10.272	0.329
.|. |	.|. |	12	0.057	0.042	11.948	0.289
.|. |	.|. |	13	0.002	-0.000	11.951	0.367
.|. |	.|. |	14	-0.043	-0.036	12.886	0.377
.|. |	.|. |	15	0.021	0.019	13.114	0.439
.|. |	.|. |	16	0.049	0.057	14.357	0.423
.|. |	.|. |	17	0.023	0.026	14.625	0.479
.|. |	.|. |	18	0.027	0.016	15.016	0.523
.|. |	.|. |	19	-0.005	0.002	15.027	0.594
.|. |	.|. |	20	-0.006	0.016	15.046	0.659
.|. |	.|. |	21	0.023	0.026	15.312	0.703
.|. |	.|. |	22	-0.014	-0.017	15.417	0.752
.|. |	.|. |	23	-0.027	-0.023	15.803	0.781
.|. |	.|. |	24	-0.025	-0.028	16.141	0.809
.|. |	.|. |	25	0.043	0.047	17.106	0.804
.|. |	.|. |	26	0.040	0.044	17.947	0.806
.|. |	.|. |	27	-0.007	-0.016	17.974	0.844
.|. |	.|. |	28	0.028	0.027	18.394	0.861
.|. |	.|* |	29	0.063	0.075	20.484	0.810
.|. |	.|. |	30	-0.004	0.009	20.492	0.846
.|. |	.|. |	31	-0.018	-0.018	20.672	0.871
.|. |	.|. |	32	0.063	0.063	22.787	0.824
*|. |	*|. |	33	-0.076	-0.069	25.870	0.728
.|. |	.|. |	34	-0.049	-0.047	27.170	0.710
.|. |	.|. |	35	0.005	-0.002	27.183	0.752
.|. |	.|. |	36	-0.055	-0.051	28.812	0.720

Appendix Table 1.15: Correlograms of the Standardised squared residuals of the variance equation of the ARMA (1, 1)-GARCH (1, 1)

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities
adjusted for 2 ARMA
term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.002	0.002	0.0016	
.|. |	.|. |	2	-0.006	-0.006	0.0185	
.|. |	.|. |	3	-0.004	-0.004	0.0263	0.871
.|. |	.|. |	4	-0.033	-0.033	0.5717	0.751
*|. |	*|. |	5	-0.070	-0.070	3.0427	0.385
.|. |	.|. |	6	0.005	0.005	3.0577	0.548
.|. |	.|. |	7	0.032	0.031	3.5791	0.611
.|. |	.|. |	8	-0.004	-0.005	3.5866	0.732
.|* |	.|* |	9	0.084	0.080	7.2131	0.407
.|. |	.|. |	10	-0.023	-0.028	7.4862	0.485
.|. |	.|. |	11	0.001	0.005	7.4869	0.587
.|. |	.|. |	12	-0.057	-0.054	9.1669	0.516
.|. |	.|. |	13	0.019	0.023	9.3492	0.590
*|. |	.|. |	14	-0.067	-0.060	11.679	0.472
.|. |	*|. |	15	-0.062	-0.066	13.662	0.398
.|. |	.|. |	16	-0.007	-0.016	13.686	0.473
.|. |	.|. |	17	0.061	0.057	15.608	0.409
.|. |	.|. |	18	-0.004	-0.012	15.616	0.480
.|. |	.|. |	19	-0.006	-0.010	15.637	0.550
.|. |	.|. |	20	0.014	0.003	15.738	0.611
.|. |	.|. |	21	0.029	0.047	16.192	0.644
.|. |	.|. |	22	0.016	0.020	16.326	0.696
.|. |	.|. |	23	0.003	0.013	16.330	0.751
.|. |	.|. |	24	0.013	0.013	16.420	0.794
.|. |	.|. |	25	-0.022	-0.017	16.681	0.825
.|. |	.|. |	26	-0.005	-0.016	16.694	0.861
.|. |	.|. |	27	0.061	0.064	18.647	0.814
.|. |	.|. |	28	-0.054	-0.059	20.204	0.782
.|* |	.|* |	29	0.080	0.080	23.590	0.653
.|. |	.|. |	30	-0.018	-0.040	23.754	0.694
.|. |	.|. |	31	-0.035	-0.026	24.410	0.708
.|. |	.|. |	32	0.048	0.064	25.652	0.693
.|. |	.|. |	33	0.009	0.007	25.700	0.736
.|. |	.|. |	34	-0.022	-0.016	25.956	0.766
.|. |	.|. |	35	0.014	0.021	26.069	0.799
.|. |	.|. |	36	-0.019	-0.030	26.268	0.826

Appendix Table 1.16: Correlograms of Standardised residuals of the estimated mean equation of the ARMA (1, 1) - EGARCH (1, 1).

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.001	0.001	0.0008	
.|. |	.|. |	2	-0.037	-0.037	0.6944	
.|. |	.|. |	3	-0.021	-0.021	0.9215	0.337
*|. |	*|. |	4	-0.077	-0.079	3.9580	0.138
.|. |	.|. |	5	-0.040	-0.042	4.7868	0.188
.|* |	.|. |	6	0.079	0.073	7.9865	0.092
.|. |	.|. |	7	-0.005	-0.011	7.9998	0.156
.|. |	.|. |	8	-0.052	-0.055	9.4022	0.152
.|. |	.|. |	9	0.021	0.017	9.6235	0.211
.|. |	.|. |	10	-0.040	-0.035	10.448	0.235
.|. |	.|. |	11	-0.009	-0.005	10.485	0.313
.|. |	.|. |	12	0.061	0.045	12.372	0.261
.|. |	.|. |	13	0.003	0.001	12.378	0.336
.|. |	.|. |	14	-0.042	-0.036	13.293	0.348
.|. |	.|. |	15	0.017	0.012	13.441	0.414
.|. |	.|. |	16	0.046	0.056	14.556	0.409
.|. |	.|. |	17	0.022	0.029	14.814	0.465
.|. |	.|. |	18	0.029	0.015	15.241	0.507
.|. |	.|. |	19	-0.004	0.001	15.249	0.578
.|. |	.|. |	20	-0.010	0.012	15.300	0.641
.|. |	.|. |	21	0.022	0.027	15.562	0.686
.|. |	.|. |	22	-0.009	-0.011	15.605	0.741
.|. |	.|. |	23	-0.025	-0.022	15.946	0.773
.|. |	.|. |	24	-0.024	-0.028	16.261	0.803
.|. |	.|. |	25	0.048	0.052	17.460	0.786
.|. |	.|. |	26	0.038	0.047	18.235	0.791
.|. |	.|. |	27	-0.007	-0.013	18.259	0.831
.|. |	.|. |	28	0.031	0.027	18.767	0.846
.|. |	.|. |	29	0.057	0.070	20.473	0.810
.|. |	.|. |	30	-0.007	0.008	20.503	0.845
.|. |	.|. |	31	-0.021	-0.021	20.735	0.869
.|. |	.|. |	32	0.059	0.059	22.628	0.830
*|. |	*|. |	33	-0.079	-0.071	26.010	0.721
.|. |	.|. |	34	-0.048	-0.050	27.252	0.706
.|. |	.|. |	35	0.007	-0.000	27.276	0.747
.|. |	.|. |	36	-0.059	-0.052	29.139	0.705

Appendix Table 1.17: Correlograms of the Standardised Squared residuals of the variance equation of the ARMA (1, 1) - GARCH (1, 1).

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.013	0.013	0.0916	
.|. |	.|. |	2	-0.000	-0.000	0.0916	
.|. |	.|. |	3	0.005	0.005	0.1029	0.748
.|. |	.|. |	4	-0.025	-0.025	0.4216	0.810
.|. |	.|. |	5	-0.063	-0.063	2.4559	0.483
.|. |	.|. |	6	0.005	0.007	2.4697	0.650
.|. |	.|. |	7	0.035	0.036	3.1050	0.684
.|. |	.|. |	8	-0.006	-0.007	3.1223	0.793
.|* |	.|. |	9	0.075	0.073	6.0257	0.537
.|. |	.|. |	10	-0.018	-0.025	6.1991	0.625
.|. |	.|. |	11	0.006	0.009	6.2163	0.718
.|. |	.|. |	12	-0.058	-0.055	7.9282	0.636
.|. |	.|. |	13	0.034	0.038	8.5126	0.667
*|. |	.|. |	14	-0.067	-0.062	10.809	0.545
.|. |	.|. |	15	-0.056	-0.057	12.445	0.491
.|. |	.|. |	16	-0.003	-0.009	12.450	0.570
.|. |	.|. |	17	0.044	0.043	13.472	0.566
.|. |	.|. |	18	-0.000	-0.005	13.472	0.638
.|. |	.|. |	19	0.004	0.001	13.482	0.703
.|. |	.|. |	20	0.014	0.002	13.589	0.755
.|. |	.|. |	21	0.031	0.048	14.096	0.778
.|. |	.|. |	22	0.024	0.023	14.391	0.810
.|. |	.|. |	23	0.003	0.014	14.396	0.852
.|. |	.|. |	24	0.015	0.013	14.512	0.882
.|. |	.|. |	25	-0.021	-0.015	14.735	0.904
.|. |	.|. |	26	-0.011	-0.021	14.802	0.926
.|. |	.|. |	27	0.052	0.057	16.240	0.908
.|. |	.|. |	28	-0.048	-0.054	17.444	0.895
.|. |	.|. |	29	0.052	0.053	18.907	0.873
.|. |	.|. |	30	-0.014	-0.035	19.013	0.898
.|. |	.|. |	31	-0.037	-0.031	19.739	0.901
.|. |	.|. |	32	0.049	0.061	21.006	0.888
.|. |	.|. |	33	0.007	0.004	21.030	0.911
.|. |	.|. |	34	-0.022	-0.018	21.284	0.925
.|. |	.|. |	35	0.028	0.036	21.717	0.934
.|. |	.|. |	36	-0.022	-0.032	21.983	0.944

Appendix Table 1.18: Correlograms of Standardised residuals of the estimated mean equation of the ARMA (1, 1) - GJR-GARCH (1, 1).

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.017</td><td>0.017</td><td>0.1503</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>-0.041</td><td>-0.041</td><td>1.0034</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>-0.031</td><td>-0.030</td><td>1.4997</td><td>0.221</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>4</td><td>-0.078</td><td>-0.079</td><td>4.5721</td><td>0.102</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.034</td><td>-0.034</td><td>5.1522</td><td>0.161</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>6</td><td>0.077</td><td>0.071</td><td>8.1978</td><td>0.085</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.008</td><td>-0.018</td><td>8.2334</td><td>0.144</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.051</td><td>-0.053</td><td>9.5384</td><td>0.145</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.016</td><td>0.016</td><td>9.6647</td><td>0.208</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.038</td><td>-0.033</td><td>10.388</td><td>0.239</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>-0.006</td><td>-0.004</td><td>10.406</td><td>0.319</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>0.055</td><td>0.040</td><td>11.967</td><td>0.287</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.001</td><td>-0.003</td><td>11.967</td><td>0.366</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.043</td><td>-0.037</td><td>12.910</td><td>0.376</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.020</td><td>0.018</td><td>13.124</td><td>0.438</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.048</td><td>0.056</td><td>14.336</td><td>0.425</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>0.022</td><td>0.024</td><td>14.585</td><td>0.482</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>0.027</td><td>0.015</td><td>14.970</td><td>0.527</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.005</td><td>0.002</td><td>14.981</td><td>0.597</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>-0.007</td><td>0.015</td><td>15.008</td><td>0.661</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>0.023</td><td>0.026</td><td>15.278</td><td>0.705</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>-0.015</td><td>-0.018</td><td>15.397</td><td>0.753</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>-0.028</td><td>-0.023</td><td>15.803</td><td>0.781</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.026</td><td>-0.028</td><td>16.155</td><td>0.808</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>0.043</td><td>0.048</td><td>17.133</td><td>0.803</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>26</td><td>0.040</td><td>0.044</td><td>17.972</td><td>0.804</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>27</td><td>-0.007</td><td>-0.016</td><td>17.997</td><td>0.843</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>28</td><td>0.028</td><td>0.027</td><td>18.419</td><td>0.860</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>29</td><td>0.061</td><td>0.075</td><td>20.426</td><td>0.812</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>-0.004</td><td>0.008</td><td>20.436</td><td>0.848</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>31</td><td>-0.019</td><td>-0.019</td><td>20.636</td><td>0.872</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>32</td><td>0.062</td><td>0.063</td><td>22.682</td><td>0.828</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>33</td><td>-0.076</td><td>-0.069</td><td>25.765</td><td>0.732</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>34</td><td>-0.049</td><td>-0.047</td><td>27.081</td><td>0.714</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>35</td><td>0.005</td><td>-0.000</td><td>27.094</td><td>0.756</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>36</td><td>-0.055</td><td>-0.050</td><td>28.709</td><td>0.724</td></tr>
</table>

Appendix Table 1.19: Correlograms of the Standardised squared residuals of the variance equation of the ARMA (1, 1) - GJR- GARCH (1, 1).

Sample: 1/25/2001 8/26/2010
Included observations: 501
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.004	0.004	0.0093	
.|. |	.|. |	2	-0.004	-0.004	0.0188	
.|. |	.|. |	3	-0.003	-0.003	0.0236	0.878
.|. |	.|. |	4	-0.031	-0.031	0.5204	0.771
*|. |	*|. |	5	-0.069	-0.069	2.9461	0.400
.|. |	.|. |	6	0.007	0.007	2.9677	0.563
.|. |	.|. |	7	0.033	0.032	3.5264	0.619
.|. |	.|. |	8	-0.003	-0.005	3.5318	0.740
.|* |	.|* |	9	0.079	0.075	6.7032	0.460
.|. |	.|. |	10	-0.024	-0.028	6.9878	0.538
.|. |	.|. |	11	-0.001	0.003	6.9885	0.638
.|. |	.|. |	12	-0.057	-0.054	8.6865	0.562
.|. |	.|. |	13	0.016	0.020	8.8210	0.638
*|. |	.|. |	14	-0.068	-0.062	11.224	0.510
.|. |	*|. |	15	-0.062	-0.066	13.201	0.432
.|. |	.|. |	16	-0.009	-0.017	13.243	0.508
.|. |	.|. |	17	0.060	0.056	15.117	0.443
.|. |	.|. |	18	-0.005	-0.013	15.131	0.515
.|. |	.|. |	19	-0.007	-0.011	15.153	0.584
.|. |	.|. |	20	0.014	0.003	15.251	0.645
.|. |	.|. |	21	0.030	0.047	15.730	0.675
.|. |	.|. |	22	0.013	0.018	15.825	0.727
.|. |	.|. |	23	0.003	0.012	15.830	0.779
.|. |	.|. |	24	0.013	0.012	15.918	0.820
.|. |	.|. |	25	-0.022	-0.017	16.164	0.848
.|. |	.|. |	26	-0.005	-0.016	16.175	0.882
.|. |	.|. |	27	0.061	0.064	18.145	0.836
.|. |	.|. |	28	-0.053	-0.059	19.652	0.808
.|* |	.|* |	29	0.077	0.077	22.814	0.695
.|. |	.|. |	30	-0.018	-0.040	22.989	0.734
.|. |	.|. |	31	-0.034	-0.025	23.625	0.747
.|. |	.|. |	32	0.045	0.061	24.730	0.738
.|. |	.|. |	33	0.008	0.005	24.765	0.778
.|. |	.|. |	34	-0.021	-0.016	25.002	0.806
.|. |	.|. |	35	0.015	0.023	25.131	0.835
.|. |	.|. |	36	-0.020	-0.030	25.354	0.858

Appendix Table 1.20: Regression results between equal-weighted turnover and stock market returns conditional on EGARCH-generated investor forecasts.

Dependent Variable: equal-weighted turnover

Method: Least Squares

Date: 12/28/11 Time: 21:02

Sample (adjusted): 2/22/2001 8/26/2010

Included observations: 497 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.027490	0.009985	-2.753021	0.0061
RT	0.007586	0.001760	4.309405	0.0000
RTI(-1)	0.009813	0.002741	3.579876	0.0004
RTI(-2)	0.003741	0.001606	2.329125	0.0203
RTI(-3)	0.003825	0.001797	2.129055	0.0338
RT_1_I(-1)	0.002111	0.001890	1.116827	0.2646
RT_1_I(-2)	-0.002187	0.002332	-0.938191	0.3486
RT_1_I(-3)	-0.003922	0.002032	-1.930164	0.0542
ABRESID(-1)	0.018745	0.006363	2.945926	0.0034
ABRESID(-2)	0.006006	0.005445	1.103061	0.2705
ABRESID(-3)	0.008054	0.005432	1.482504	0.1389

R-squared	0.211466	Mean dependent var	-0.000232
Adjusted R-squared	0.195241	S.D. dependent var	0.103165
S.E. of regression	0.092547	Akaike info criterion	-1.900308
Sum squared resid	4.162598	Schwarz criterion	-1.807160
Log likelihood	483.2265	Hannan-Quinn criter.	-1.863748
F-statistic	13.03333	Durbin-Watson stat	1.218235
Prob(F-statistic)	0.000000		

Appendix Table 1.21: Regression results between value-weighted turnover and stock market returns conditional on EGARCH-generated investor forecasts.

Dependent Variable: value-weighted turnover

Method: Least Squares

Date: 12/28/11 Time: 21:11

Sample (adjusted): 2/22/2001 8/26/2010

Included observations: 497 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007693	0.004778	-1.609992	0.1080
RT	0.002539	0.000725	3.501334	0.0005
RTI(-1)	0.003247	0.000908	3.576448	0.0004
RTI(-2)	0.001582	0.000741	2.136161	0.0332
RTI(-3)	0.001046	0.000803	1.301546	0.1937
RT_1_I(-1)	0.000895	0.000815	1.097601	0.2729
RT_1_I(-2)	-0.000116	0.000946	-0.122174	0.9028
RT_1_I(-3)	-0.001086	0.000842	-1.290206	0.1976
ABRESID(-1)	0.007128	0.002659	2.681104	0.0076
ABRESID(-2)	2.78E-05	0.002345	0.011837	0.9906
ABRESID(-3)	0.001481	0.002547	0.581384	0.5613

R-squared	0.126361	Mean dependent var	-0.000206
Adjusted R-squared	0.108385	S.D. dependent var	0.045192
S.E. of regression	0.042672	Akaike info criterion	-3.448644
Sum squared resid	0.884975	Schwarz criterion	-3.355496
Log likelihood	867.9880	Hannan-Quinn criter.	-3.412083
F-statistic	7.029390	Durbin-Watson stat	1.291677
Prob(F-statistic)	0.000000		

Appendix Table 1.22: Regression results between equal-weighted turnover and stock market returns conditional on GJR-GARCH-generated investor forecasts.

Dependent Variable: equal-weighted turnover

Method: Least Squares

Date: 12/28/11 Time: 21:25

Sample (adjusted): 2/22/2001 8/26/2010

Included observations: 497 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.028652	0.010202	-2.808446	0.0052
RT	0.007582	0.001755	4.320039	0.0000
RTI(-1)	0.009666	0.002735	3.533964	0.0004
RTI(-2)	0.003777	0.001647	2.293107	0.0223
RTI(-3)	0.003858	0.001805	2.137513	0.0331
RT_1_I(-1)	0.002156	0.001867	1.154535	0.2488
RT_1_I(-2)	-0.002448	0.002275	-1.075807	0.2825
RT_1_I(-3)	-0.004388	0.002015	-2.177390	0.0299
ABRESID(-1)	0.018942	0.006758	2.802960	0.0053
ABRESID(-2)	0.006783	0.005490	1.235615	0.2172
ABRESID(-3)	0.008537	0.005489	1.555123	0.1206

R-squared	0.216282	Mean dependent var	-0.000232
Adjusted R-squared	0.200156	S.D. dependent var	0.103165
S.E. of regression	0.092264	Akaike info criterion	-1.906435
Sum squared resid	4.137173	Schwarz criterion	-1.813287
Log likelihood	484.7490	Hannan-Quinn criter.	-1.869874
F-statistic	13.41209	Durbin-Watson stat	1.224312
Prob(F-statistic)	0.000000		

Appendix Table 1.23: Regression results between value-weighted turnover and stock market returns conditional on GJR-GARCH-generated forecasts.

Dependent Variable: value-weighted turnover

Method: Least Squares

Date: 12/28/11 Time: 21:26

Sample (adjusted): 2/22/2001 8/26/2010

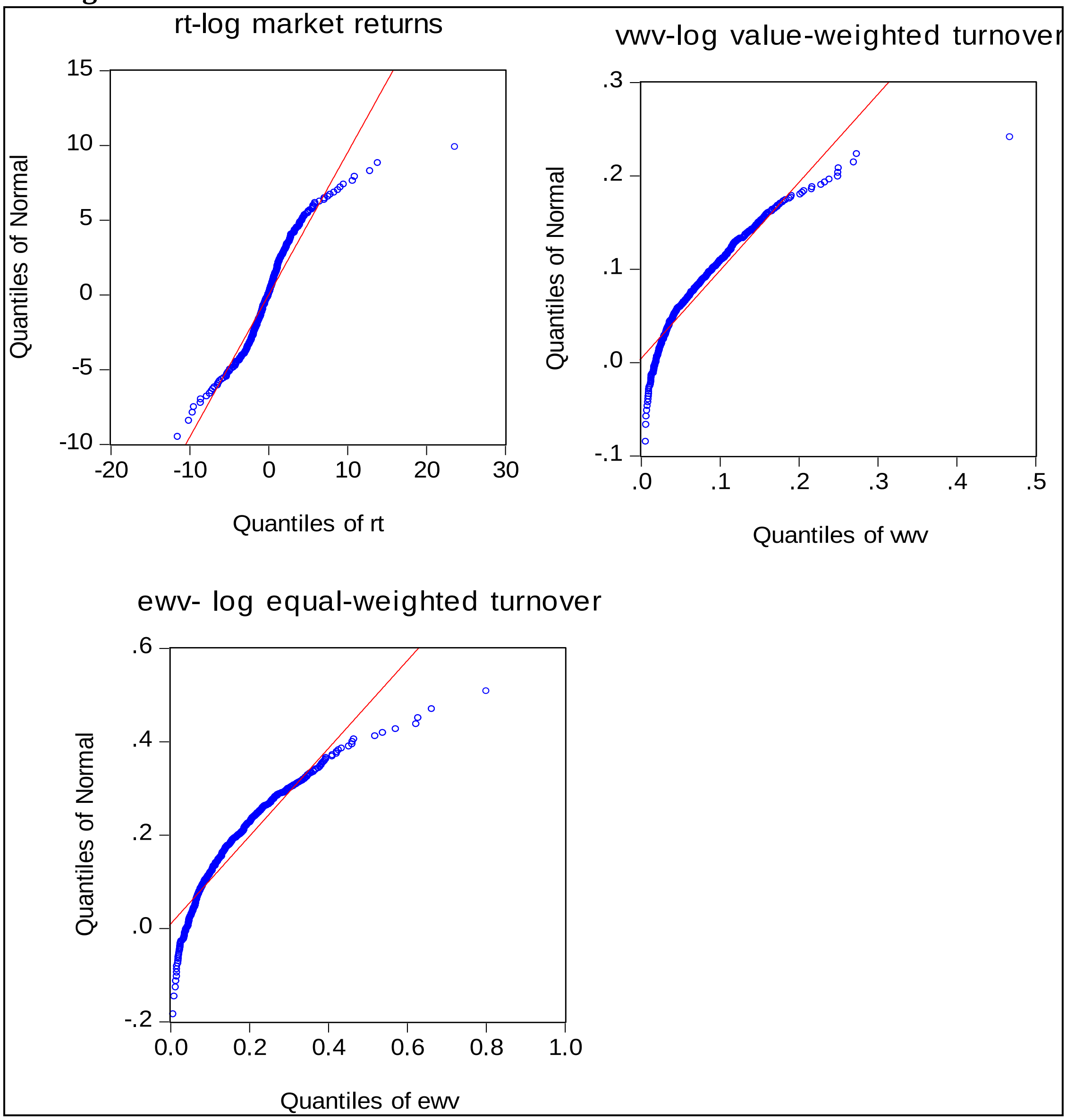
Included observations: 497 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)

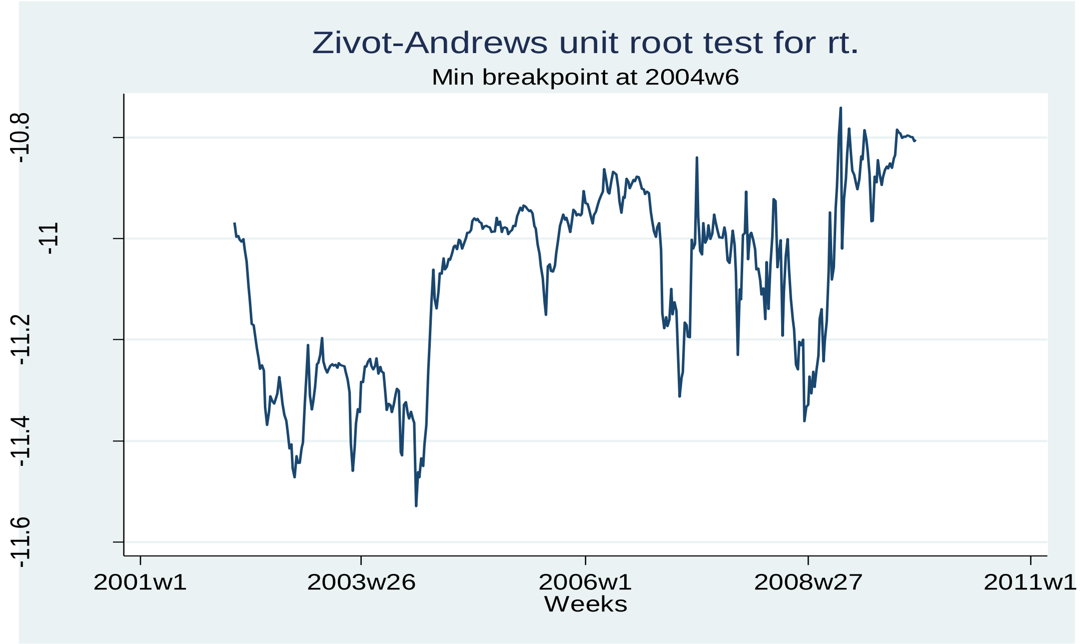
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007860	0.004960	-1.584600	0.1137
RT	0.002536	0.000724	3.504611	0.0005
RTI(-1)	0.003204	0.000924	3.468599	0.0006
RTI(-2)	0.001609	0.000752	2.141288	0.0327
RTI(-3)	0.001077	0.000805	1.336946	0.1819
RT_1_I(-1)	0.000926	0.000803	1.153850	0.2491
RT_1_I(-2)	-0.000207	0.000930	-0.222499	0.8240
RT_1_I(-3)	-0.001266	0.000844	-1.501078	0.1340
ABRESID(-1)	0.006995	0.002749	2.544368	0.0113
ABRESID(-2)	0.000251	0.002369	0.106081	0.9156
ABRESID(-3)	0.001563	0.002552	0.612548	0.5405

R-squared	0.128026	Mean dependent var	-0.000206
Adjusted R-squared	0.110085	S.D. dependent var	0.045192
S.E. of regression	0.042632	Akaike info criterion	-3.450552
Sum squared resid	0.883288	Schwarz criterion	-3.357404
Log likelihood	868.4621	Hannan-Quinn criter.	-3.413991
F-statistic	7.135637	Durbin-Watson stat	1.292851
Prob(F-statistic)	0.000000		

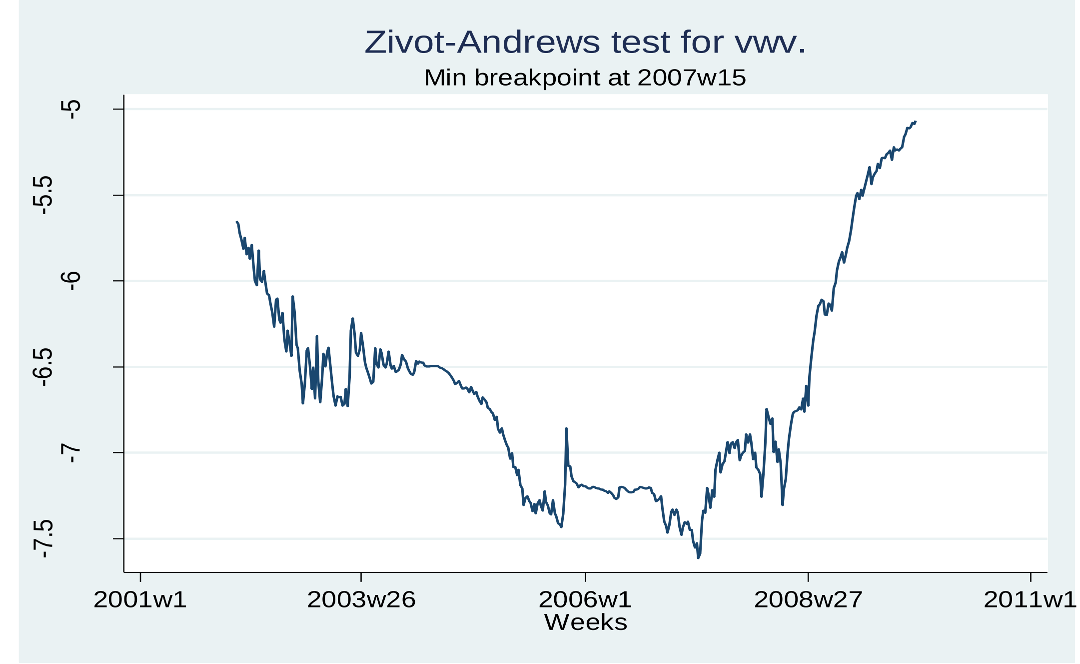
Appendix Figure 1.1: Quantile-Quantile Plots of the NSE-20 share index returns and trading volume.



Appendix Figure 1.2 : Zivot-Andrews unit root test for market returns



Appendix Figure 1.3: Zivot-Andrews test for value-weighted turnover



Appendix Figure 1.4: Zivot-Andrews test for equal-weighted turnover