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Investor Behavior Biases and Stock Market Reaction in Kenya

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Abstract

A challenge to EMH is that individuals often overreact and underreact to news causing stock markets to react according to investor behaviour in their investment decision making. Generally, the study determined the effect of investor behaviour on stock market reaction of listed companies in Kenya. Specifically, the study determined the effect of investor herd behaviour on stock market reactions of listed companies in Kenya; determined the effect of investor loss aversion on stock market reactions of listed companies in Kenya; determined the effect of investor mental accounting on stock market reactions of listed companies in Kenya; and determined the effect of investor overconfidence on stock market reactions of listed companies in Kenya. The target population was 67 listed companies at the Nairobi Securities Exchange. A sample of 48 listed companies was used for analysis. Secondary data extracted from NSE historical data of listed companies for the period 2004 to 2016 was used for analysis. The study adopted quantitative research design. Panel data regression analysis model was used. The results indicated that herd behaviour did not have a significant effect on stock market reaction. However, loss aversion, mental accounting and overconfidence had significant effect on stock market reaction in Kenya.

JEL classification numbers: C91, D03, D84
Keywords: Herding Behaviour; Loss Aversion; Overconfidence; Mental Accounting; Overreaction; Stock Market Reaction; Under-reaction.

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1 Introduction

Behavioural models have been developed to explain price momentum and reversal in returns as a continuation followed by reversal in returns to reflect the dynamic interaction between news watchers and momentum traders predicted by the behavioral model (Lin, 2010). Investors are much more sensitive to reductions in financial wealth than to increases, also known as loss aversion. After prior gains, an investor becomes less loss averse because the prior gains will cushion any subsequent loss an investor might incur in future therefore making it more bearable in case it incurs loss after incurring gains. Conversely, after a prior loss, an investor becomes more loss averse: after being burned by the initial loss, investor become sensitive to additional setbacks and will avoid further investments (Barberis, Huang & Santos, 2001).

Herding is regarded as a rational strategy for less sophisticated investors, who try to imitate the activities of successful investors since the use of their own information and knowledge lead to greater cost (Khan, Hassairi & Viviani, 2011), thus the presence of extreme market movements could exacerbate this behavior. The cost and time of processing the amount of information generated during those periods would be higher than usual, increasing the incentives to herd. Extreme down-market movements and periods of stress have been linked to herding both directly and indirectly through market volatility to show that crises significantly increase market volatility. Mobarek, Mollah and Keasey (2014) opines that herding is more pronounced when market returns, trading volume and return volatility are high. Herd behavior is the most accepted psychological context in the creation of speculative bubbles in the financial markets because of inclination to observe winners mainly when good performance repeats itself.

An aspect of investor herd behavior is noise trading which follows the fact that investors with short time horizon are manipulating the stock prices more than long-term investors. One of the main arguments of behavioral finance is that some properties of asset prices are most probably regarded as deviations from fundamental value and caused by irrational investors called noise traders (Uygur & Taş, 2014). Noise trader theory postulates that sentiment traders have greater impact during high-sentiment periods than during low-sentiment periods, and sentiment traders miscalculate the variance of returns undermining the mean-variance relation. Noise trading existence in the stock markets can increase price volatility and consequently the risk associated with investing in the stock market and the risk premia (De Long, 2005). The authors supported the idea that rational speculators in the presence of positive feedback investors might proceed to buy today in the hope of selling to noise traders at a higher price tomorrow, moving the prices even further away from their fundamentals. Individual investors are the culprits of stock market reactions due to noise trading (De Long, Shleifer, Summers & Waldmann, 1990).

Myopic loss aversion explanation rests on two behavioral principles: loss aversion and mental accounting. In loss aversion, people tend to be more sensitive to decreases in their wealth than increases. This can help explain the tendency of investors to hold on to loss making stocks while selling winning stocks too early (Shefrin & Statman, 2011). Mental accounting describes a tendency of people to place events into different mental accounts based on superficial attributes like dividend paying stocks will be more preferred causing prices to rise.

Daniel, Hirshleifer and Subrahmanyam (1998) proposed a theory of security markets based on investor overconfidence, about the precision of private information and biased self-attribution, which causes changes in investors' confidence as a function of their investment outcomes, which leads to market underreactions and overreactions. The authors indicated that investor behaviour has been proposed as an explanation for stock market reactions such as momentum effects in the intermediate (short) horizon and return reversals in the long horizon. Irrational investors destabilize markets, by buying when prices are high and selling when they are low, whereas rational investors move the prices closer to their fundamental value, by buying when they are low and selling when they are high (Blasco, Corredor, & Ferreruela, 2012).

Mental accounting refers to the implicit method investors use to code and evaluate financial outcomes, transactions, investments, gambles etc. (Benartzi & Thaler, 1995). Mental accounting behavior describes the propensity of people to place some events into different mental accounts based on superficial attributes. People sometimes disconnect decisions that should in principle be combined. Mental accounting is applied to explain why investors are likely to abstain from regarding his or her reference point for a stock. When a stock is purchased, a new mental account for that stock is opened. The succession score is then kept on this account indicating gains or losses relative to purchase price. A normative frame identifies that there is no substantive distinction between returns of stocks. A combination of mental accounting (Thaler, 1985) and risk seeking in the domain of losses (Kahneman & Tversky, 1979) lead investors to hold onto losing investments and sell winners. Many private investors engage in mental accounting, meaning they make distinctions in their head that do not exist financially. Often, losses incurred are viewed separately from paper losses. This means that investors sell stocks from their portfolio too soon when they earn a profit and too late when they incur a loss. Turning a paper profit into real profits makes investors happy, but investors shy away from turning a paper loss into a real loss.

Information asymmetry drives price volatility and uninformed investors largely tend to follow the market trend, buying when prices rise and selling when they fall. Investor behavior explains excess volatility of stock prices based on short run post-earnings announcement drift (Daniel & Hirshleifer, 2015). Many uninformed traders will simply follow any trend that they believe exists in share price behaviour and this trend chasing increases the volatility displayed by the market as these investors are unaware of the fundamental prices of the stock they are trading and so are unable to stop trading when the value is reached. Investor behavior has strong evidence to cause stock market reactions and explains the causes of market anomalies and is therefore an effective investment strategy by measuring investor irrational behaviours to determine return predictability in the financial markets.

1.1 Statement of the Problem

The decisions of investors in the stock market play an important role in determining the market trend, which then affects the economy (Wan, Cheng & Yang, 2014). Abnormal returns occur when stock prices are driven away from fundamental values, then the prices gradually revert to the fundamental values. Short-term price momentum trends after earnings announcements and long-term price reversals after earnings trends explain how investor irrational behaviours drive stock prices away from the fundamental values. Investor behavior variables therefore explains stock market reactions to determine whether profit opportunities exist because of stock market reactions based on patterns of return predictability. Stock market anomalies indicate either market inefficiency i.e. profit opportunities or inadequacies in the underlying asset-pricing model. Systematic risk, size effect, liquidity (buy-ask spreads) and value effect do not hold up in different sample periods and have lost predictive power to be used as an investment strategy. Investor behavior model on stock market reactions, therefore, is an effective investment strategy to determine returns predictability in the financial markets (Debondt & Thaler, 1985).

Investors at the NSE equity market lost close to Kshs. 500 billion in 2016 to a market value of Kshs. 1.931 trillion as share prices declined by 25.35% compared to 2015 which was valued at Kshs. 2.42 trillion (CMA). The demand for stocks has been limited by a continued wait-and-see attitude by investors amid persistent volatility. In violation of the Bayes rules, individuals tend to overweigh recent information and under weigh prior data or base rate, hence overreaction (DeBondt & Thaler, 1985).

Mbaluka (2008) established the existence of behavioural effects on individual investment decision making process at the NSE. Werah (2006) suggested that the behaviour of investors at the NSE is to some extent irrational regarding fundamental estimations because of anomalies such as herd behaviour, regret aversion, overconfidence and anchoring. Aduda and Muimi (2011) confirmed evidence of investor over-reaction and under-reaction at the NSE. Thirikwa and Olweny (2015) found that the magnitude of the impact of the market performance on the deviation of individual stock returns was also impacted by the market capitalization and the book-to-market value was relatively low. Previous studies have looked at the impact of investor behaviour biases on investment decisions, investor performance and stock market developments. An investor behavior model is needed to explain the observed pattern of returns that explains stock market reactions. The research will use investor behavioral variables of herding, loss aversion, mental accounting and overconfidence to determine predictability of abnormal returns in Kenya. The research gap therefore is to determine the effect of investor behavior biases on stock returns in Kenya.

1.2 General Objective

The general objective is to determine the effect of investor behavior biases on stock market reaction in Kenya.

1.3 Specific Objectives

1. To determine the effect of herd behavior on stock market reaction in Kenya.
2. To determine the effect of loss aversion on stock market reaction in Kenya.
3. To determine the effect of mental accounting on stock market reaction in Kenya.
4. To determine the effect of overconfidence on stock market reaction in Kenya.

1.4 Research Hypotheses

This study will seek to address the following pertinent research hypotheses;

H_{01}: Herd behavior has no significant effect on stock market reaction in Kenya.

H_{02}: Loss aversion has no significant effect of on stock market reaction in Kenya

H_{03}: Mental accounting has no significant effect on stock market reaction in Kenya

H_{04}: Overconfidence has no significant effect on stock market reaction in Kenya

1.5 Significance of Study

This research will guide Capital Markets Authority on the effect of investor behavior on stock market reactions. The study will be useful to policy makers and investors in the stock markets to consider behavioural factors on their investment decisions. The study ensures economic stability can be enhanced by policy makers through putting in policies that enhance effective asset allocation in the capital markets. It will ensure the government and private planners establish ex ante rules to improve choices and efficiency, including disclosure, reporting, advertising and default-option-setting regulations. It will ensure the government should avoid actions that exacerbate investor biases because deviations in stock prices increase volatility in the stock market. CMA will use this study to monitor and regulate by ensuring listed companies to offer sufficient information promptly for the investors to reduce investor irrational behaviors.

Companies going public can use the findings of this study to understand how investor behavior influence the price of securities and hence can set realistic prices that will attract the investors they target without distorting the market. The findings of this study will help stockbrokers and fund managers to understand investor behavior and advise the investors appropriately. The Nairobi Securities Exchange and other market players can use these findings as a basis of investor education and minimization of noise trading in the Kenyan.

1.6 Scope of Study

The study determined the effect of investor behavior on stock market reactions in Kenya. The population for this study comprised of all the 67 listed companies at the NSE for the period of 2004 to 2016. A sample of 48 listed companies was used in this study. The period 2004 to 2016 was sufficient to cover stock market reaction during periods of market stress, recovery periods of the market and the current price declines experienced at the NSE.

1.7 Limitation of the Study

The process of collecting the secondary data brought challenges of companies that were listed for a short period. The study sampled companies that had been listed for at least three years prior to the date of analysis. This was to enable the research to deal with dynamics of time components and to capture investor behaviour variables and stock market reactions in Kenya. The research therefore sampled 48 of the 67 listed companies. This presented a 72% of the target population over the sample period.

2 Literature Review

2.1 Theoretical Literature

Kahneman and Tversky's (1979) hypothesized the descriptive model of decision making under risk, prospect theory, which used experimental evidence to argue that people got utility from gains and losses in wealth, rather than from absolute levels. The specific finding known as loss aversion was that people were more sensitive to losses than they were to gains. Since the framework was inter-temporal, the research also made use of more recent evidence on dynamic aspects of loss aversion. This evidence suggested that the degree of loss aversion depended on prior gains and losses: A loss that comes after prior gains was less painful than usual, because it was cushioned by those earlier gains. On the other hand, a loss that came after other losses was more painful than usual: After being burned by the first loss, people became more sensitive to additional setbacks.

Rozin and Royzman (2001) found that loss aversion had been linked to the negativity bias. The negativity bias described that people paid more attention to negative information than to positive information. Barberis and Huang (2001) explained that loss aversion referred to the difference level of mental penalty people have from a similar size loss or gain. Barberis and Huang (2001) showed that a loss coming after prior gain was proved less painful than usual while a loss arriving after a loss seemed to be more painful than usual. Barberis and Thaler (2003) showed evidence showing that people were more distressed at the prospect of losses than they are pleased by equivalent gains Lehenkari and Perttunen (2004) found that both positive and negative returns in the past could boost the negative relationship between the selling trend and capital losses of investors, suggesting that investors were loss averse.

This anomaly of human judgment was demonstrated in several experiments by psychologists. Kahneman and Tversky (1979) explained that there was no problem in judgment and decision making which was more prevalent and more potentially catastrophic than overconfidence. Plous (1993) explained that people were overconfident. The author explains discrepancies between accuracy and confidence were not related to a decision maker's intelligence. Daniel, Hirshleifer and Subrahmanyam (1997) proposed a theory based on investor overconfidence and biased self-attribution to explain several of the securities returns patterns that seemed anomalous from the perspective of efficient markets with rational investors.

Daniel, Hirshleifer and Subrahmanyam (1998) objective proposed a theory of securities market under-reaction and overreaction based on two well-known psychological biases: investor overconfidence about the precision of private information; and biased self-attribution, which caused asymmetric shifts in investors' confidence as a function of their investment outcomes. The theory also offered several untested implications and implications for corporate financial policy.

Daniel and Hirshleifer (2015) discussed the role of overconfidence as an explanation asset prices to displaying patterns of predictability that were difficult to reconcile with rational-expectations-based theories of price formation. The finding indicated anomalies in financial markets were unprofitable active trading and patterns of return predictability that were puzzling from the perspective of traditional purely rational models.

Herding is said to be present in a market when investors opt to imitate the trading practices of those they consider to be better informed, rather than acting upon their own beliefs and private information. A very early reference of herding theory was the classic paper by Grossman and Stiglitz (1976) which showed that uninformed traders in a market context could become informed through the price in such a way that private information was aggregated correctly and efficiently. Two streams of theories identified in literature to investigate the herd behavior, one was investor herd behavior toward a stock and other was market-wide herding. As per herding toward stock, individuals or a group of investors focused only on a subset of securities at the same time by neglecting other securities with identical characteristics.

Chiang and Zheng (2010) explained that herd behaviour in financial markets was of interest to both economists and practitioners. Economists were interested in herding because of the behavioral effect on stock prices. It affected their return and risk characteristics and thus had consequences for asset pricing models. Practitioners instead were interested in herding among investors since it created profitable trading opportunities. Furthermore, due to herding in the market investors needed a larger number of securities that created a lower degree of correlation to reach the same degree of diversification.

Thaler (1985) developed new concepts in three distinct areas: coding gains and losses, evaluating purchases i.e. transaction utility and budgetary rules called mental accounting theory. The author hypothesized that people tried to code outcomes to make themselves as happy as possible i.e. the hedonic editing hypothesis. The hedonic editing hypothesis characterized decision makers as value maximizers who mentally segregated or integrated outcomes depending on which mental representation was more desirable. On mental accounting and mental budgeting, the author suggested that people under-consumed hedonic, luxury goods. The author argued that hedonically pleasurable luxuries were often under-consumed for self-control reasons, which was why they were attractive gifts.

2.2 Conceptual Framework

Cooper and Schindler (2011) defined dependent variable as a variable that is measured, predicted, or otherwise monitored and is expected to be affected by manipulation of an independent variable. Independent variable is also defined as a variable that is manipulated by the researcher, and the manipulation causes an effect on the dependent variable. Figure 2.1 showed the conceptual framework of the study and depicted the interrelationship between the study variables. The dependent variable in the study was the Stock Market Reaction. The independent variable was investor behaviour variables. Investor behaviour variables were represented by four constructs which include: Herd Behaviour, Loss Aversion, Mental Accounting and Overconfidence.

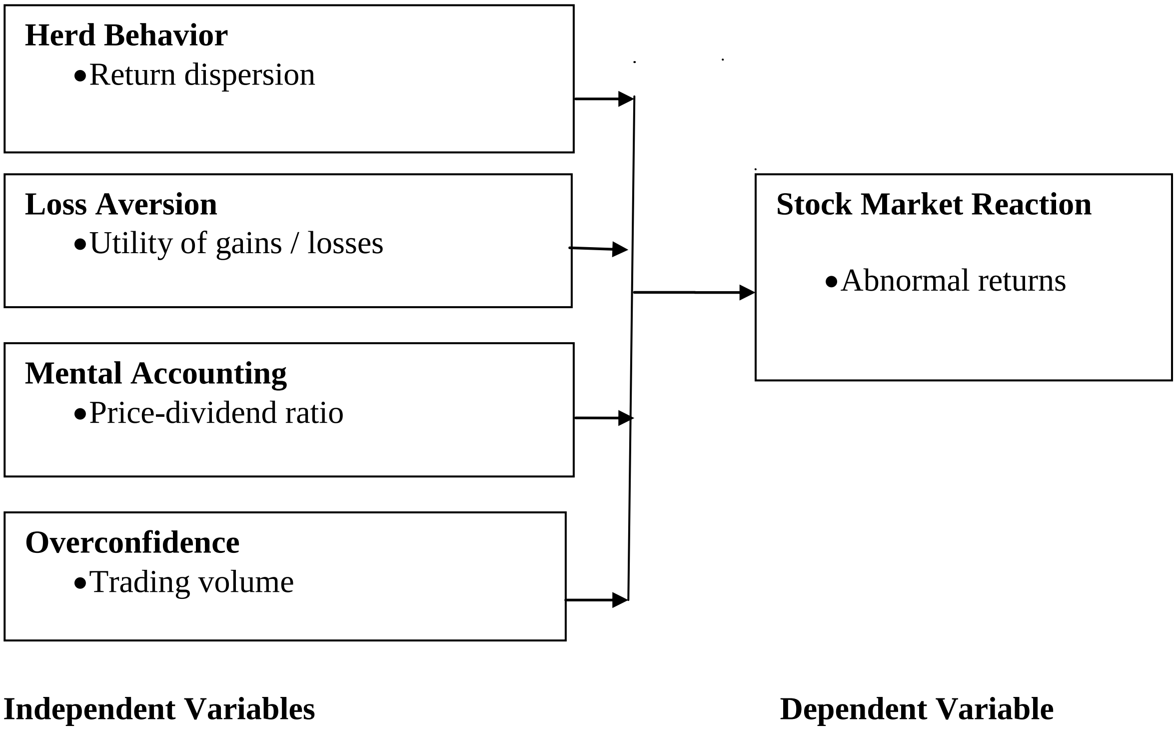

Figure 2.1: Conceptual Framework

Independent variables were operationalised as follows: Herd Behavior variable was measured using return dispersion (Thirika & Olweny, 2015); Loss Aversion variable was measured using utility of gains/losses (Barberis & Huang, 2001); Mental Accounting variable was measured using price dividend ratio (Barberis & Huang, 2001); and Overconfidence variable was measured using trading volume (Adel & Mariem, 2013). The dependent variable, stock market reaction variable was measured using abnormal returns based on DeBondt and Thaler (1985). The objective of the research determined the effect of investor behavior on stock market reactions in Kenya.

2.3 Empirical Literature

This section reviews literature from prior scholars regarding the effect of investor behaviour variables: herd behavior, loss aversion, mental accounting and overconfidence on stock market reaction, the dependent variable

DeBondt and Thaler (1985) objective was to investigate whether investor behavior affected stock prices. The independent variable was excess adjusted residual returns between the winner and loser portfolios. The dependent variable was cumulative abnormal returns. The study used quantitative research design. Panel data regression model was adopted. The findings indicated that based on CRSP monthly return data; there was consistency with overreaction hypothesis that shed new light on the January returns earned by prior winners and losers.

Thirikwa and Olweny (2015) objective was to investigate the determinants of herding at the Nairobi securities exchange. The context was Kenya. The research design used was quantitative research design. The target population was companies listed at the NSE. The independent variables were domestic market returns, market capitalization, book to market value and external market returns. The dependent variable was market wide herding measured using CSAD. The methodology adopted was quantitative research design i.e. longitudinal survey design i.e. panel data regression analysis was used to analyze data. The authors focused on the way deviations on the returns on individual stocks is influenced by the market performance (returns), market capitalization of the firms, the book-to-market value of the firms and the external market performance. The study used daily time series data for the period between 2008 and June 2015. The empirical analysis was an Ordinal Least Square (OLS) regression analysis. The main findings of the research were as follows: The stock returns were fat tailed (leptokurtic) and not normally distributed. The results showed evidence of herding in the NSE around market performance, market capitalization and book-to-market value. The result showed that the magnitude of the impact of the market performance on the deviation on individual stock returns, measured by β_3, is relatively high at 9.475 and significant at 1%. Deviations in the stock returns was also impacted by the market capitalization and the Book-to-market value, though both relatively low, at =0.670 and = -0.242 at 1% significant level relatively.

Barberis and Huang (2001) objective was to study equilibrium firm-level stock returns in two economies: one in which investors were loss averse over the fluctuations of their stock portfolio, and another in which they were loss averse over the fluctuations of individual stocks that they own. The independent variable was utility of gains and losses stock and price-dividend ratio. The dependent variable was Stock Returns for individual and portfolio stocks. Quantitative research design and the model specification was panel data regression model was used. The findings were that the typical individual stock return has a high mean and excess volatility, and there was a large value premium in the cross section which could to some extent, be captured by a commonly used multifactor model.

Adel and Mariem (2013) objective was to study the impact of overconfidence bias on the decisions of investors, specifically to evaluate the relationship between the bias, trading volume and volatility. Context was Tunis. The empirical study on a sample of 27 companies listed on the stock exchange in Tunis, observed over the period, which ran from 2002 until 2010. The dependent variable was investor overconfidence. Independent variables were trading volume, market return, volatility and turnover. The results achieved through the application of tests and

VAR modeling ARMA-EGARCH indicated the importance of confidence bias in the analysis of characteristics of the Tunisian financial market.

3 Methodology

3.1 Data Processing and Analysis

The panel data regression model adopted is the Auto Regressive Distributed Lag model because of panels in which both T, the number of time series observations, and N, the number of groups are quite large and of the same order of magnitude. Mean Group estimators estimate N separate regressions and calculate the coefficient means or to pool the data and assume that the slope of coefficients and error variances are identical. Pooled Mean Group estimator constraints the long run coefficients to be identical but allows short run coefficients and error variances to differ across groups. Pool Mean Group estimator considers both cases where the independent variables are stationary or where they follow unit root process, and for both cases derive the asymptotic distribution of the Pool Mean Group estimator as T tends to infinity.

3.1.1 Measurement of Study Variables

Secondary data was collected from historical data at NSE for the period 2004 to 2016. This approach was guided by econometric theory that advocated for panel data analysis to achieve better regression results (Baltagi, Bratberg & Holmås, 2005). One of the main advantages of panel data was that it enabled the researcher to control against unobserved heterogeneity and provided the researcher with both cross-sectional and time-series dimensions; which reduced the likelihood of bias in the parameter estimators. Historical data on stock prices, volume traded, number of deals and price dividend ratio was analysed in excel and used to compute the formulas relevant for the study variables in the sample selected listed companies across time.

Descriptive statistics included measures of central tendency, dispersion and skewedness were used to summarize and profile stock market reaction, herd behaviour, loss aversion, mental accounting and overconfidence variables for the study. Panel regression model was used in the analysis. E Views version 9 software was used in the analysis to determine the effect of investor behaviour on stock market reaction. Presentation of study results was done by use of tables, graphs and box plots.

3.1.2 Measurement of Study Variables

The study adopted stock market reaction as the measure for dependent variable. Herd behavior, loss aversion, mental accounting and overconfidence constituted investor behavior which were the independent variables for the study. This section provided details of how each of the study variables was measured and operationalized**.**

Stock Market Reactions

Stock market reaction was measured using abnormal returns. Excess return AR_{it} were computed as the difference between the stock return and the market portfolio return to get market adjusted return. Abnormal return was measured as follows:
Abnormal return = Observed return – Expected return

$$AR_{i,t} = R_{i,t} - R_{m,t} \quad (3.1)$$

Where:
R_{it} = Actual return observed for all the 48 listed stocks in the 13 year period
R_{mt} = the equal-weighted return of the entire 20 share index.
t = the 13 year-period, i = the 48 sampled listed companies at NSE
Market return constant R_{mt} was subtracted from $R_{it.}$ There was no risk adjustment except for movements of the market as a whole and the adjustment wass identical for all stocks (De Bondt & Thaler, 1985).

Herd Behavior

Herd behavior was measured using return dispersions based on Cross Sectional Absolute Deviations (CSAD) method (Thirika & Olweny, 2015). CSAD was expressed as

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|r_{it} - r_{mt}| \quad (3.2)$$

CSAD is the measure of dispersion where:
N is the number of companies in the sample,
r_{it} = the observed stock return on firm i for 13-year t,
and r_{mt} = the cross-sectional average return on year t.
i = the 48 companies sampled
t = the 13 year period from 2004 to 2016
This meant that the dispersions would decrease or at least increase at a less-than-proportional rate with the market return. Herd behaviour existed when there was a small difference between the returns of individual stock and the market index.

Loss Aversion

Utility of gains or losses of prior returns was used to measure loss aversion variable (Barberis & Huang, 2001). The gain or loss on stock *i* between time *t* and *t* + 1 was measured as follows:

$$X_{i,t+1} = S_{i,t}R_{i,t+1} - S_{i,t}R_{f,t} \quad (3.3)$$

Where:

$X_{i,t+1}$ = the measures the gain or loss on stock *i* between time *t* and time *t*_1, a positive value indicating a gain and a negative value, a loss.
$S_{i,t}$ = the reference state of the value of the investor's holdings of stock *i* at time *t*
R_{it+1} = the future expected return (one-year lead)
$R_{f,t}$ = the risk free rate (Treasury bill rate)
In words, the gain was the value of stock *i* at time *t* + 1 minus its value at time *t* multiplied by the risk-free rate. Expected return led by one month minus equals to market return minus risk free rate.

Mental Accounting
Mental Accounting was measured using price-dividend ratio. Price-dividend ratio is financial ratio that indicates how much a company pays out in dividends each year relative to its share price. The formula was as follows:

$$\frac{P_0}{D_1} = K \qquad (3.4)$$

Where:
P_0 = the price of stock
D_0 = the dividend paid that year and K is the price dividend ratio.
A stock with a high price-dividend ratio i.e. a growth stock was often one that has done well in the past, accumulating prior gains for the investor, who then views it as less risky and requires a lower average return. A stock with a low price-dividend ratio was a value stock had often had dismal prior performance, burning the investor, who now views it as riskier, and required a higher average return. The mental accounting variable was first calculated by forming five portfolios. The portfolios formation was based on the price-divided ratio annually. These portfolios were rebalanced each year to form new portfolios. Barberis and Huang (2001) subtracted the average returns of the portfolio of the companies that had the highest price-divided ratio from the average returns of the companies that had the lowest price-divided ratio. This resulted in a portfolio referred to as difference portfolio. The intention of creating this portfolio was to assess whether mental accounts formed on the basis of the price-divided ratio have any explanatory power on the market reaction. It was to assess whether the companies that pay lower divided are able to beat the high paying divided companies. The formula was as follows:

$$SMR = PortfolioA – PortfolioB \qquad (3.5)$$

Where: Portfolios A were companies with low price-dividend ratio
Portfolios B were companies with high price-dividend ratio

Stocks with low price-dividend ratios i.e. dividend yield had higher average returns than stocks with high price-dividend ratios. Multifactor models that had been shown to use the value premium in actual data and matches empirical features of aggregate asset return (Barberis & Huang, 2001). In equilibrium, aggregate stock returns had a high mean, excess volatility, and were moderately predictable in the time series, while the risk-free rate was constant and low.

Overconfidence

Overconfidence was measured using trading volume values divided by the number of deals to ascertain turnover rate. Turnover rate was used as a measure of volume of transactions and number of deals (Adel & Mariem, 2013). Excessive trading of shares on confidence contributed to excessive volatility (Adel & Mariem, 2013). Overconfidence was measured by turnover as follows:

$$\text{Turnover Rate} = \frac{n_{it}}{N_{it}} \tag{3.6}$$

Where:

n_{it} = the number of shares traded of stock i (volume traded per year);

N_{it} = the number of exchanges of stock i (number of deals per year); t was time 13-year period; and i was the 48 sampled listed company at the NSE.

Table 3.1 Summary of Measuring Variables

Dependent variable	**Measure**	**Proxy**	**Data**
Stock Market Reaction	(Abnormal Returns)	$AR_{i,t} = R_{i,t} - R_{m,t}$	Past returns
Independent Variables	**Measure**	**Proxy**	**Data**
Herd Behaviour	Return dispersion	$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\lvert r_{it} - r_{mt}\rvert$	Past returns
Loss Aversion	Utility of gains/ losses	Prior gains and losses	Returns
		$X_{i,t+1} = S_{i,t}R_{i,t+1} - S_{i,t}R_{f,t}$	
Mental Accounting	Price-dividend ratio	Value premium (Portfolios A are companies with low price-dividend ratio) **less** (Portfolios B are companies with high price–dividend ratio)	Past returns
Overconfidence	Trading volume & Number of deals	Turnover rate $= \frac{n_{it}}{N_{it}}$	Trading volume and number of deals

De Bondt and Thaler (1985); Adel and Mariem (2013); Barberis and Huang (2001); Thirika and Olweny (2015).

3.1.3 Statistical Model

Panel data regression models was used to pool data observations on a cross-section of the sampled 48 listed companies under study over a period of thirteen years. The study used panel regression models to analyze secondary data as the secondary data collected will exhibit both time series and cross-sectional dimensions. Stock market reactions variable was modelled because of herding, loss aversion, mental accounting and overconfidence. The study determined the effect investor behavior on stock market reactions in Kenya, panel regression equation will be specified as follows:

$$SMR_{it} = \alpha_{it} + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \mu_{it} \quad (3.7)$$

Where: SMR_{it} is Stock Returns as measured by Abnormal Returns to determine stock market reaction**,** X is the investor behaviour variables (Herd Behaviour, Loss Aversion, Mental Accounting and Overconfidence). The variable effect on the stock market to determine if there is overreaction or under-reaction in the stock market. α_0 is the intercept term, α_i are the independent variables, μ_{it} is the error term (the time-varying disturbance term is serially uncorrelated with mean zero and constant variance). *i* = 1… 67 companies listed at the NSE, *t* = time in years from 2004 to 2016 to determine the effects of investor behavior on stock market reactions.

4 Results and Discussion

4.1 Descriptive Statistics for Dependent and Independent Variables

Table 4.1 Descriptive Statistics

	Stock Market Reaction	Herd Behavior	Loss Aversion	Mental Accounting	Overconfidence
Mean	0.239585	7.446169	-2.120756	1.271245	7.452941
Median	-0.325554	4.978227	0.109167	0.515701	7.599967
Maximum	122.4242	122.4242	958.8919	53.17610	14.38127
Minimum	-97.94357	0.002961	-1199.735	-31.50250	-0.572519
Std. Dev.	12.10587	9.547525	107.5521	8.298008	1.825437
Skewness	0.512158	4.451179	-0.791119	1.762223	-0.355976
Kurtosis	19.61086	32.89297	18.30443	14.78702	4.150125
Jarque-Bera	73258.50	257316.5	62141.37	40033.52	483.9462
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1520.883	47268.28	-13360.76	8069.866	47311.27
Sum Sq. Dev.	930165.6	578562.3	72863450	437035.0	21149.60

Table 4.1 presents some elementary tests of descriptive statistics and normality. From the results, the standard deviation of the variables was found to be outside the acceptable range of 3 standard deviations for stock market reactions, investor herd behavior, investor loss aversion, investor mental accounting variables while investor overconfidence was within the normal distribution bound. The results of standard deviation were supported by those of skewness which is a measure of dispersion with only investor overconfidence having a skewness close to zero.

The skewness value for all the other variables showed that the variables are not all normally distributed since their value of skewness disperse from zero significantly. In extension, the result of kurtosis was away from the expected value of 4 for a normal distribution for stock market reactions, investor herd behavior, loss aversion, mental accounting variables and only overconfidence had a value of 4. The probabilities of the Jarque-bera are all away from the value of one (1) which means that all the variables are not normally distributed per this test statistic which weighs the information between skewness and kurtosis. The interpretation is that special methods that takes care of the dispersions from normality was adopted to minimize any bias that may arise.

The results for descriptive statistics for stock market reactions showed that for mean is 0.239585, median is 0.325554, maximum is 122.4242, minimum is -97.94357, standard deviation is 12.10587, skewness is 0.512158, kurtosis is 19.61086 and Jarque-Bera is 73258.50. The probability is 0 meaning the data is not normally distributed. When data is normally distributed the p-value is 1.

The results for descriptive statistics for Herd Behavior showed that for mean is 7.446169, median is 4.978227, maximum is 122.4242, minimum is 0.002961, standard deviation is 9.547525, skewness is 4.451179, kurtosis is 32.89297 and Jarque-Bera is 257316.5. The probability is 0 meaning the data is not normally distributed. When data is normally distributed the p-value is 1.

The results for descriptive statistics for Loss Aversion showed that for mean is -2.120756, median is 0.109167, maximum is 958.8919, minimum is -1199.735, standard deviation is 107.5521, skewness is -0.791119, kurtosis is 18.30443 and Jarque-Bera is 62141.37. The probability is 0 meaning the data is not normally distributed. When data is normally distributed the p-value is 1.

The results for descriptive statistics for Mental Accounting showed that for mean is -1.271245, median is 0.515701, maximum is 53.17610, minimum is -31.50250, standard deviation is 8.29808, skewness is 1.762223, kurtosis is 14.78702 and

Jarque-Bera is 40033.52. The probability is 0 meaning the data is not normally distributed. When data is normally distributed the p-value is 1.

The results for descriptive statistics for Overconfidence showed that for mean is 7.452941, median is 7.599967, maximum is 14.38127, minimum is -0.572519, standard deviation is 1.825437, skewness is 0.355976, kurtosis is 4.150125 and Jarque-Bera is 483.9462. The probability is 0 meaning the data is not normally distributed. When data is normally distributed, the p value is 1.

As evidence in this section, the variables data has departures from the normal distribution. One of the key reason is that the variables could be suffering from the integration problem. If a time series variable is integrated, it means it values could be wondering around. This would cause the normality assumption of a variable to be violated. The interpretation from the results in this section was that before the use of these variables in further analysis, there was the need to utilize special tools that help us to check whether by introducing the lag structure for the individual variables in order to update the financial information from the previous periods, help improve the distribution of variables before further analysis. Some of the more formal techniques that are used to check whether updating a variable's information, by including lags is the execution of the unit root tests. The unit roots are the formal test of a variable stationarity in time series analysis. A series is said to be (weakly or covariance) stationary if the mean and auto-covariance of the series do not depend on time. Any series that is not stationary is said to be non-stationary. The next section diagnosed this problem before the regression analysis was conducted. So the key interest in time series studies is to see whether by trying to eliminate departures from normality one would arrive at some meaningful analysis even though the original variables are skewed.

4.2 Model Specification Tests

4.2.1 Unit Root Test

The results from the unit root test for all the cross-sections in the variable stock market reaction in table 4.2 above shows that all the 48 cross sections in the were stationary. The first part of the table presents the common unit root test developed by Levin, Lin and Chu (2002).

The test shows that considered simultaneously all the cross-section are stationary for the stock market reaction variable. In other words, they do not have the unit root problem since the null hypothesis of unit root is rejected as depicted by the significant p-value of 0.0000. The lower section presents three test of stationarity in panel data setting. These are Im, Pesaran and Shin (2003), ADF - Fisher Chi-square Maddala and Wu (1999), PP - Fisher Chi-square (Choi, (2001). These tests assume the test of unit root on individual cross sections. As depicted by the p-values which are very statistically significant, the null hypothesis of non-stationarity was rejected. The interpretation was that the stock market reaction variable was stationary in the two cases of test. In conclusion, the test of stationarity is important because it help to identify the order of integration of a variable and avoid spurious regression. In this case the marker reaction variable is integrated of order zero (0).

Table 4.2 Unit Root Test

Panel unit root test: Summary				
Series: Stock Market Reaction				
Method	Statistic	P-value	C-sections	Obser vation
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-96.0960	0.0000	48	6292
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin Wstat	-87.1475	0.0000	48	6292
ADF - Fisher Chi-square	3582.55	0.0000	48	6292
PP - Fisher Chi-square	3697.44	0.0000	48	6300
Series: Herd Behavior				
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chut*	-67.8411	0.0000	48	6295
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-62.9233	0.0000	48	6295
ADF - Fisher Chi-square	2729.07	0.0000	48	6295
PP - Fisher Chi-square	2874.81	0.0000	48	6300
Series: Loss Aversion				
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chut*	-94.5903	0.0000	48	6236
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-86.6497	0.0000	48	6236
ADF - Fisher Chi-square	3511.31	0.0000	48	6236
PP - Fisher Chi-square	3807.87	0.0000	48	6252
Series: Mental Accounting				
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-91.3319	0.0000	48	6300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-83.5193	0.0000	48	6300
ADF - Fisher Chi-square	3642.26	0.0000	48	6300
PP - Fisher Chi-square	3642.29	0.0000	48	6300
Series: Overconfidence				
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.00532	0.0000	48	6250

Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-15.5181	0.0000	48	6250
ADF - Fisher Chi-square	499.442	0.0000	48	6250
PP - Fisher Chi-square	1075.90	0.0000	48	6300

4.2.2 Cross-Sectional Dependence Test (CSDT)

In estimating panel models, it is normally assumed that the cross-sections used are independent especially when the number of observations (N) is large. Findings by various researchers have found that cross-sectional dependence in estimation is frequently present in panel setting. Failing to take care of cross-sectional dependence in the estimation process can have serious consequence. This is the case because the unaccounted for residual dependence results in estimator inefficiency and invalid test results. Table 4.3 above presents the results on cross-sectional independence of individuals in a panel series. The null hypothesis of no cross-sectional dependence (correlation) is tested against that of cross-sectional dependence. From the test statistics employed Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD it was evident that there is cross-sectional dependence in this variable. The p-value gives a strong evidence against the null hypothesis. The interpretation is that some information in each of the cross-sections has the tendency to flow it other cross-sections.

Table 4.3 Cross-Section Dependence (Correlation) (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	Statistic	Degrees of freedom	P-value
Stock Market Reaction			
Breusch-Pagan LM	1812.800	1128	0.0000
Pesaran scaled LM	13.40706		0.0000
Bias-corrected scaled LM	13.25222		0.0000
Pesaran CD	16.10668		0.0000
Null hypothesis: No Cross-Section Dependence (Correlation)			
Herd Behavior			
Breusch-Pagan LM	5607.528	1128	0.0000
Pesaran scaled LM	93.30050		0.0000
Bias-corrected scaled LM	93.14465		0.0000
Pesaran CD	53.15335		0.0000
Null hypothesis: No Cross-Section Dependence (Correlation)			
Series: Loss Aversion			
Breusch-Pagan LM	127767.1	1128	0.0000
Pesaran scaled LM	2665.223		0.0000

Bias-corrected scaled LM	2665.068		0.0000
Pesaran CD	350.3421		0.0000
Null hypothesis: No Cross-section Dependence (Correlation)			
Series: Mental Accounting			
Breusch-Pagan LM	46266.44	1128	0.0000
Pesaran scaled LM	949.3251		0.0000
Bias-corrected scaled LM	949.1703		0.0000
Pesaran CD	203.4395		0.0000
Null hypothesis: No cross-section dependence (correlation)			
Series: Overconfidence			
Breusch-Pagan LM	2113.472	1128	0.0000
Pesaran scaled LM	19.73735		0.0000
Bias-corrected scaled LM	19.58251		0.0000
Pesaran CD	16.34837		0.0000

4.2.3 Multicollinearity Test / Correlation Test

Table 4.4 shows the pair-wise correlation matrix. Brook (2002) asserts that multicollinearity is the problem that occurs when the explanatory variables are very highly correlated with each other. If there is no multicollinearity, then adding or removing a variable from a regression equation would not cause the values of the coefficients on the other variables to change.

Table 4.4 Pair-wise Correlation Test

	Stock market reaction	Herd Behavior	Loss Aversion	Mental Accounting	Overconfidence
Stock market reactions	1.000000				
Investor herd behavior	0.148535	1.000000			
Investor loss aversion	-0.826320	-0.168335	1.000000		
Investor mental accounting	0.035048	0.050570	-0.026333	1.000000	
Investor overconfidence	0.017307	-0.038426	-0.032091	-0.054848	1.000000

The result for pair-wise correlation shows that there is no multicollinearity problem since the highest correlation between the independent variables was

5.0570 % between investor herd behavior and investor loss aversion and the least one was -5.4848 % between mental accounting and investor loss aversion. Thus, all the independent variables were retained for further analysis.

4.2.4 Causality Tests

Table 4.5 above presents the results for granger causality. The table presents the results for the direction of causality between the dependent and the independent variables. The two-way causality results are presented in the appendices due to the large size of the table. Given the results all the p-values are statistically significant part from only two pairs; investor overconfidence does not granger cause stock market reactions and investor mental accounting does not granger cause stock market reactions.

Table 4.5 Granger Causality Test

Pairwise Granger Causality Tests
Lags: 4

Null Hypothesis:	**Observations**	**F-Statistic**	**P-value**
Investor herding behavior does not Granger Cause Stock Market Reactions	6156	2.77857	0.0254
Stock Market Reactions does not Granger Cause Investor Herding Behavior		7.60604	4.E-06
Investor loss aversion does not Granger Cause Stock Market Reactions	6108	61.8647	3.E-51
Stock Market Reactions does not Granger Cause Investor Loss Aversion		34.3290	2.E-28
Mental accounting does not Granger Cause Stock Market Reactions	6156	0.57503	0.6808
Stock Market Reactions does not Granger Cause Investor Mental accounting		8.48472	8.E-07
Investor overconfidence does not Granger Cause Stock Market Reactions	6156	0.85898	0.4877
Stock Market Reactions does not Granger Cause Investor Overconfidence		3.99537	0.0031

The interpretation was that a dynamic method that could handle lagged structure in the model was necessary. One of such a laborious model is the autoregressive distributed lag model (ARDL). Granger (1969) noted that, a variable x is said to granger-cause a variable y if, given the past values of y, past values of x are useful for predicting y. Failing to reject the null hypothesis is same as failing to reject the hypothesis that x does not granger-cause y.

4.2.5 Cointegration Test

Table 4.6 Pedroni Cointegration Test

Series: Stock Market Reactions, Investor Herd Behavior, Investor Loss Aversion, Investor Mental Accounting and Investor Overconfidence

Null Hypothesis: No Cointegration

Alternative Hypothesis: Common AR coefficients (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel V-Statistic	-0.327263	0.6283	-4.508593	1.0000
Panel Rho-Statistic	-97.55195	0.0000	-92.15360	0.0000
Panel PP-Statistic	-71.27764	0.0000	-68.22089	0.0000
Panel ADF-Statistic	-42.10477	0.0000	-41.06860	0.0000

Alternative hypothesis: Individual AR coefficients (between-dimension)

	Statistic	Prob.
Group Rho-Statistic	-91.97357	0.0000
Group PP-Statistic	-80.75326	0.0000
Group ADF-Statistic	-46.70912	0.0000

Table 4.6 presents a set of Pedroni tests of a cointegrating vector. The table presents two sets of test statistics. The first part contains eight sets of test statistics under the null of homogeneity among all the panels. The word homogeneity meaning that the test of cointegration assume the data set as a single continuous structure and that all panels follow the same properties. These tests are namely; Panel v-Statistic, Panel Rho-Statistic Panel PP-Statistic and Panel ADF-Statistic. The second part of the table presents the test statistics under the assumption of heterogeneity. Heterogeneity here refers to the test of cointegration on each individual cross-section separately. These tests are namely; Group rho-Statistic, Group PP-Statistic and Group ADF-Statistic.

All the tests of cointegration in table 4.14 reject the null of no cointegration apart from only two as inferred by the p-values. Since most of the p-value had a value of zero, it was necessary to ensure that the techniques used for the model estimation considers the aspect of cointegration. The interpretation was that in this research study, cointegration was a key analytical tool.

4.3 Regression Results

Panel Fully Modified Ordinary Least Squares (FMOLS) Method

Table 4.7 Pooled Estimation (FMOLS)

Dependent Variable: Stock Market Reaction

Independent Variable	Coefficient	Std. Error	t-Statistic	P-value
Investor Herd Behavior	0.021848	0.009060	2.411394	0.0159
Investor Loss Aversion	-0.094232	0.000780	-120.7703	0.0000
Investor Mental Accounting	0.029103	0.010051	2.895353	0.0038
Investor Overconfidence	-0.189160	0.054455	-3.473729	0.0005

R-squared	0.697559	Mean dependent var	0.204549
Adjusted R-squared	0.692692	S.D. dependent var	12.01348
S.E. of regression	6.659714	Sum squared residual	272852.2
Long-run variance	41.67899		

Table 4.7 presents the co-integration results generated by employing the pooled estimation in the context of panel fully modified least square method. It was advanced by Phillips and Hansen (1990) who used it to handle time series problems. Phillips and Moon (1999) later employed the same technique to solve co-integration in panel setting. This cointegration technique was purely developed to handle variables that are co-integrated of the same order in economics and especially those with a single unit root.

However, in this paper, all the variables were found to be integrated of order zero but never the less they were subjected to the same technique to bring out the difference between this traditional technique and the modern one that was primarily employed in this paper as the primary analytical tool. It assumes homogeneity in the all the cross sections. In other words, all the parameters are identical across all individuals and in our case all the companies included. The interesting finding was that the results are very close to the pooled mean group (which was the primary estimator) in this study. It not surprising though since pooled estimation in (FMOLS) is already nested in pooled mean group. Further, apart from the coefficient of investor herd behavior that is slightly different others have retained their signs. The coefficients also fall in the same confidence interval.

Herd Behaviour

From the regression result in table 4.7 above the long run coefficient of investor herding behavior was found to be 0.021848. This value shows that holding other variables in the model constant, an increase in the investor behavior by one unit causes an effect of stock market reaction to decrease by 0.021848 units. The positive effect shows that there is an inverse relationship between investor herd behavior and stock market reaction.

The coefficient was also found to be statistically significant with a t-statistic value of 2.411394. In econometrics and statistical analysis, a t-statistic of 1.96 and above is normally accepted to be the threshold for significant. The standard error was found to be 0.009060 and the p-value was found to be 0.0159. The interpretation for this model was that in the Kenyan stock market, the investor herd behavior has a statistically significant effect on stock market reaction in the long-run horizon. The findings indicate that investor herd behavior has a positive significant effect on stock market reactions in Kenya.

Loss Aversion

From the regression results in table 4.7 above the long run coefficient of investor loss aversion was found to be -0.094232. This value shows that holding other variables in the model constant, an increase in the investor loss aversion by one unit causes the stock market reaction to decrease by -0.094232 percent. The negative effect shows that there is an inverse relationship between investor loss aversion and stock market reaction.

The coefficient was also found to be statistically significant with a t-statistic value of -120.7703. In econometrics and statistical analysis, a t-statistic of 1.96 and above is normally accepted to be the threshold for significant. The standard error was found to be 0.000780 and the p-value was found to be 0.0000. The interpretation was that in Kenya the investor loss aversion has a negative statistically significant effect on stock market reaction in the long-run horizon. This imply that contradicts those of in loss aversion would cause a reduction market reaction.

Mental Accounting

From the regression results in table 4.7 above the long run coefficient of investor mental accounting was found to be 0.029103. This value shows that holding other variables in the model constant, an increase in the investor mental accounting by one unit causes the market reaction to increase by a value of 0.029103 percent. The positive effect shows that investors views the companies that pay less divided as the ones that will have a high return in the future thus these stocks would be termed as more viable.

The coefficient was also found to be statistically significant with a t-statistic value of 0.029103. In econometrics and statistical analysis, a t-statistic of 1.96 and above is normally accepted to be the threshold for statistical significance. The t-statistics was 2.895353. The standard error was found to be 0.010051 and the p-value was found to be 0.0038. The interpretation was that in Kenya, investor mental accounting variable has a positive statistically significant effect on stock market reaction in the long-run horizon. This imply that increase in loss aversion would cause an increase in market reaction. These findings support those of Barberis and Huang (2001) who found that the portfolio formed to mimic the effect of mental accounting had had a positive effect on stock market reaction. The interpretation was that the firms that pay less divided can subsequently beat those that pay high divided in an attempt to attract investors.

Overconfidence

From the regression results in table 4.7 above the long run coefficient of Investor overconfidence was found to be -0.189160. This value shows that holding other variables in the model constant, an increase by one percent causes stock market reaction to increase by a value of -0.189160 percent. The negative effect shows that there is a direct relationship between investor overconfidence and stock market reaction.

The coefficient was also found to be statistically significant with a t-statistic value of -3.473729. In econometrics and statistical analysis, a t-statistic of 1.96 and above is normally accepted to be the threshold for statistical significance. The standard error was found to be 0.054455 and the p-value was found to be 0.0005. The interpretation was that in Kenya the Investor overconfidence has a negative statistically significant effect on stock market reaction in the long-run horizon. This imply that increase in Investor overconfidence would cause an increase in market reaction.

4.4 Hypothesis One Test

Table 4.8 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic 2.411394, F-statistic 5.814823 and Chi-square 5.814823. These values are statistically insignificant as showed by p-values of 0.0159, 0.0159 and 0.0159 respectively. The null hypothesis of the coefficient being zero (C (1) = 0) is not rejected. The interpretation is that the individual effect of investor heard behavior is statistically insignificant. In other word investor herd behavior contribute very little to the market reaction.

Table 4.8 H01: Investor herd behaviour has no significant effect on stock market reactions in Kenya

Wald Test:			
Test Statistic	Value	Degrees of Freedom	Probability
t-statistic	2.411394	6152	0.0159
F-statistic	5.814823	(1, 6152)	0.0159
Chi-square	5.814823	1	0.0159
Null Hypothesis: C(1)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(1)		0.021848	0.009060
Restrictions are linear in coefficients.			

Hypothesis Two Test

Table 4.9 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic -120.7703, F-statistic 14585.46 and Chi-square 14585.46. These values are statistically significant as showed by p-values of 0.0000, 0.0000 and 0.0000 respectively. The null hypothesis of the coefficient being zero **(**C (2) = 0) is rejected. The interpretation is that the individual effect of investor loss aversion is statistically significant. In other word investor loss aversion contribute very significantly to the market reaction.

Table 4.9 H02: Investor loss aversion has no significant effect on stock market reactions in Kenya.

Wald Test:			
Test Statistic	Value	Degrees of freedom	Probability
t-statistic	-120.7703	6152	0.0000
F-statistic	14585.46	(1, 6152)	0.0000
Chi-square	14585.46	1	0.0000
Null Hypothesis: C(2)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(2)		-0.094232	0.000780
Restrictions are linear in coefficients.			

Hypothesis Three Test

Table 4.10 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic 2.895353, F-statistic 8.383071 and Chi-square 8.383071. These values are statistically significant as showed by p-values of 0.0038, 0.0038 and 0.0038 respectively. The null hypothesis of the coefficient being zero **(**C (3) = 0) is rejected. The interpretation is that the individual effect of investor mental accounting is statistically significant. In other words, investor mental accounting contribute very significantly to the stock market reaction.

Table 4.10 H_{03}: Investor mental accounting has no significant effect on stock market reaction in Kenya

Wald Test:			
Test Statistic	Value	Degrees of freedom	Probability
t-statistic	2.895353	6152	0.0038
F-statistic	8.383071	(1, 6152)	0.0038
Chi-square	8.383071	1	0.0038
Null Hypothesis: C(3)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(3)		0.029103	0.010051
Restrictions are linear in coefficients.			

Hypothesis Four Test

Table 4.11 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic -3.473729, F-statistic 12.06679 and Chi-square 12.06679. These values are statistically significant as showed by p-values of respectively 0.0005, 0.0005 and 0.0005. The null hypothesis of the coefficient being zero **(**C (4) = 0) is rejected. The interpretation is that the individual effect of investor overconfidence is statistically significant. In other word investor overconfidence contribute very significantly to the market reaction.

Table 4.11 H04: Investor overconfidence has no significant effect on stock market reactions of listed companies in Kenya.

Wald Test:			
Test Statistic	Value	Degrees of freedom	Probability

t-statistic	-3.473729	6152	0.0005
F-statistic	12.06679	(1, 6152)	0.0005
Chi-square	12.06679	1	0.0005

Null Hypothesis: C(4)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4)	-0.189160	0.054455

Restrictions are linear in coefficients.

4.5 Post Estimation Tests

Table 4.12 Model Residuals Unit Root Test

Method	Statistic	P-value	Cross-sections	Observation
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-87.4422	0.0000	48	6199
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-79.6550	0.0000	48	6199
ADF - Fisher Chi-square	3482.17	0.0000	48	6199
PP - Fisher Chi-square	3523.01	0.0000	48	6204

Table 4.12 presents the results on the unit root test of the residuals after the model estimation. From the results, it was clear that the residuals were stationary since the nulls of unit root both under common root process and individual unit root process test were rejected. This argument is reinforced by the p-values. The interpretation was that the model was optimally identified.

4.6 Summary of Results and Discussions

This chapter presented the results and discussions. The chapter focused on descriptive statistics, stationarity test, Cross-Sectional Dependence Test (CSDT), multicollenearity test, cointegration test, regression results, error correction and trend and confidence interval. The chapter also presented results from other related regression techniques. The techniques included Fully Modified Ordinary Least Square method (FMOLS) and Dynamic Ordinary Least Square method

(DOLS). All these techniques were employed to determine the effect of investor behavioral aspects on the market reaction in Kenya.

The study established that there is an effect of investor behavior on stock market reaction at Nairobi Securities Exchange in Kenya. The findings were arrived at after multidimensional analysis of data. The data was first subjected to descriptive statistrics to establish normality test that is essential for convergence of the parameters to their true values. All the variables were r found to have normally problem. The measures of central tendency employed Jarque-bera, skewness and kurtosis revealed that the distribution of the variables was normal. Normality in statistical analysis is important for the parameters in the model or in a system to collapse very first to their true value. The variables were further subjected to other pre-estimation econometric analytical tools. One of these tools is the unit root test, which was employed to assess the stationarity of the variables. The study found that all the five variables were found to be stationary at level as presented by the panel unit roots tests tables in chapter four. Stationarity is important to identify the integration order of a variable. When stationarity is ignored it can lead to spurious regression in the analysis and give the wrong inference.

This study also took an extra step to assess the cross-sectional dependence of the different cross-section in each of the five variables variable. From the test statistics employed Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD it was evident that there was cross-sectional dependence all the variables. The p-value gave a strong evidence against the null hypothesis that there was no cross-sectional dependence. The interpretation was that some information in each of the cross-sections had the tendency to flow it other cross-sections. However, this problem was eliminated by employing the pooling and group estimators together.

The study employed Pair-wise correlation analysis to test for multicollinearity among the independent variables. The study conducted granger causality to test the direction of causality. The research revealed that some of the variables exhibited granger causality to one another. Having established the presence of lagged structure in the data, the study employed the Autoregressive Distributed Lag Model, as the model estimation method which can combine both stationary and non-stationary time-series data by selecting the optimal lag structure of the dependent and the independent variables to achieve optimal convergence. This method is also able to nest one of the most efficient estimator known as pooled mean group estimator. In pooled mean group, the research could strike a balance between the pooling method of parameter estimation and the grouping method. It was shown that in ARDL setting both the long-run and short-run models explained to large extent the variation of market reaction. It was also notable from the ARDL method that the model was correcting the dis-equilibrium at a very high speed of 95.5183%. The results of the confidence interval for this model showed that all the coefficient fall within the confidence interval bounds.

The model estimation was also extended to another two methods which are also used to handle panel settings in analysis. These two techniques are Fully Modified Ordinary Least Square (FMOLS) and Dynamic Ordinary Least Square (DOLS) methods. These two methods revealed that our primary method is good at striking a balance between pooling and grouping. They compare very well apart from the slight deviation. The other interesting revelation was that the coefficients of the two extra models falls within the confidence interval of the ARDL. This further reign forces our findings.

5 Conclusion

The study concluded that in the NSE, Kenyan stock market, herd behavior has a no significant effect on stock market reaction. The study concludes that the herd behavior has statistically insignificant effect on stock market reaction. This variable was insignificant in the primary model that uses the pooled mean group as an estimator as well as the other two techniques that considers the pooling and the group aspect separately.

The study concluded that in Kenyan stock market, loss aversion has a significant effect on stock market reaction. The study concludes that the investor loss aversion has a statistically significant effect on market reaction. This variable was significant in the primary model that uses the pooled mean group as an estimator as well as the other two techniques that considers the pooling and the group aspect separately.

The study concluded that in Kenyan stock market mental accounting has a significant effect on stock market reaction. The study concludes that the investor mental accounting has a statistically significant effect on stock market reaction. This variable was significant in the primary model that used the pooled mean group as the estimator as well as the other two techniques that considers the pooling and the group aspect separately.

The study concluded that in Kenyan stock market, overconfidence bias has a significant effect on stock market reaction. The study concludes that the investor overconfidence has a statistically significant effect on stock market reaction. This variable was significant in the primary model that used the pooled mean group as an estimator as well as the other two techniques that consider the pooling and the group aspect separately.

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