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INVESTOR BEHAVIOUR AND STOCK MARKET REACTION IN KENYA

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Abstract:
Nairobi Securities Exchange has witnessed cases of stock market reactions as a result of extreme price volatility which point to the possibility of underlying inefficiencies that impacts on the shareholder value. Such market reactions are as a result of irrational investor behavior leading to market inefficiencies. A challenge to Efficient Market Hypothesis 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 indicate that investor herd behaviour does not have a significant effect on stock market reaction. However, investor loss aversion, investor mental accounting and investor overconfidence have significant effect on stock market reaction in Kenya.

JEL: E22; G11

Keywords: herd behavior; loss aversion; mental accounting; overconfidence; stock market efficiency

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1. Introduction

Kenya being an African country practices collectivist culture that influences the investor investment decisions. The Nairobi Securities Exchange has witnessed certain cases of extreme price volatility which points to the possibility of underlying inefficiencies which impacts on the shareholder value. Using analysis of monthly returns on stocks, evidence of overreaction and under-reactions of investors in the Nairobi Stock Exchange has been witnessed (Aduda and Muimi, 2011). In Kenya, there have been incidences of stock inefficiencies in the Nairobi Securities Exchange caused by investor irrational behavior. The 2008 Safaricom IPO which was overwhelmingly oversubscribed traded at below Kshs. 5 for over 5 years after the IPO with the shares going for as low as Kshs. 2.00. The scramble for Safaricom's stock was an overreaction behavior witnessed among investors anchored by salient past events of the lucrative returns seen in the 2006 KenGen IPO where the power producer's share price was more than triple after listing the offer at Kshs.11.90 per share. Mbaluka (2008) establishes the existence of behavioural effects on individual investment decision making process.

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. Overconfident investors may more readily sell winners, because the run-up they expected had occurred, but incrementally was less willing to sell losers, because they remain confident that the run-up will eventually occur and this is witnessed in the Mumias Sugar Company share investements at the NSE. Kenyan investors bought the Mumias Sugar Company stock at its peak and held it prospecting profitability of the stock returns in future. Individual investors had their investment decisions affected by loss aversion bias. Overreaction and underreaction of share prices have been witnessed in the Mumias Sugar Company share and it presents a very bitter lesson on how unabated mismanagement can destroy shareholder wealth. Behavioural factors such as representativeness, overconfidence, anchoring, gambler's fallacy, availability bias, loss aversion, regret aversion and mental accounting affected the decisions of investors operating at the NSE (Waweru, Munyoki & Uliana, 2008).

Loss aversion affects investor decisions at the NSE, investors are frame dependent and loss averse (Mbaluka, Muthama & Kalunda, 2012). Loss aversion behavior was witnessed with investors that held shares at Uchumi Supermarkets Limited. The investors after learning in early 2000s when Uchumi started experiencing financial and operational difficulties that were caused by a sub-optimal expansion strategy, poor internal control systems and mismanagement that the share prices were losing value, the investors still held the shares in the hope that the financial performance will improve. Human psychology played a role in investment choices based on assessment of returns and investor behavior influences investor investment decisions at the NSE (Kotieno, 2012).

Aduda and Muimi (2011) tested for investor rationality for companies listed at the Nairobi Stock Exchange and the results were consistent with the notion of overreaction,

showing that investors overreact to both good and bad news. However, the authors did not examine the investor behavior variables to find out whether it had an effect on stock market reaction or not. Aduda and Muimi (2011) tested overreaction by investors to news and performance of companies listed at the Nairobi Securities Exchange as an anomaly that has been proven in other markets. Kenya Airways stock closed 2016 at 19.39% higher than 2015. Herding behaviour was witnessed on the KQ share towards the end of the year 2016 when one big investor decided to buy the shares at Kshs.2 million and everyone else imitated him by buying KQ shares pushing the prices higher.

Investigations on whether NSE is efficient and in what form of efficiency have been considered by previous research studies. Kiprono (2014) finds evidence of significant abnormal price reaction around the earnings announcement periods suggesting that earnings announcements do contain relevant information. Earnings announcements provide a yardstick that can be utilized by the market to assess the wealth and profitability of a firm. If the market is efficient, then any new information released is instantaneously reflected in the share price. Therefore, as earnings are publicly announced, the share price should immediately reflect this announcement and therefore deny investors any above-average risk-adjusted profits. However, investor behavior after the announcement of earnings determine the demand and supply based on purchases and sells of stock and that will be determined in the research on its effect on stock market reaction in Kenya. Wamae (2013) investigated herding, prospecting, risk aversion and anchoring and found that all the factors affect investment decision, with herding having the most impact, followed by prospecting; anchoring and finally the risk aversion factor had the least impact on investment decisions.

2. 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). Stock market reactions 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 overreaction 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 on stock market reactions in Kenya.

3. General Objective

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

3.1 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.

3.2 Research Hypotheses

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

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

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

3.3 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.

3.4 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.

3.5 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.

4. Research Methodology

4.1 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.

4.2 Measurement of Study Variables

Herding behavior, Loss aversion behaviour, mental accounting behaviour and overconfidence behaviour are the independent variables. Stock market reaction is the dependent variable.

4.3 Stock Market Reactions

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

$$AR_{i,t} = R_{i,t} - R_{m,t} \quad (1)$$

Where for the monthly period t, market return constant R_{mt} is subtracted from R_{it}. R_{mt} is the equal-weighted return of the entire 20 share index. There is no risk adjustment except for movements of the market as a whole and the adjustment is identical for all stocks (De Bondt & Thaler, 1985); (Boussaidi, 2017).

4.4 Investor Herd Behaviour

Investor herd behavior was measured using return dispersions using Cross Sectional Absolute Deviations (CSAD) method (Thirika & Olweny, 2015). CSAD is expressed as

$$CSAD_{it} = |r_{it} - r_{mt}| \quad (2)$$

CSAD is the measure of dispersion, where N is the number of firms in the aggregate market portfolio, r_{it} is the observed stock return on firm i for month t, and r_{mt} is the cross-sectional average return on month t. This means that the dispersions will decrease or at least increase at a less-than-proportional rate with the market return. Herding exists when there is a small difference between the returns of individual stock and the market index.

4.5 Loss Aversion Behaviour

Loss aversion behaviour is measured using utility of gains or losses of prior returns to measure loss aversion behavior (Barberis & Huang, 2001). The gain or loss on stock *i* between time *t* and *t* + 1 was measured as follows:

$$X_{i,t+1} = S_{i,t}R_{i,t+1} - S_{i,t}R_{f,t}$$

Where *Xi*, *t*_1 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. The utility the investor receives from this gain or loss is given by the function v, and it is added up across all stocks owned by the investor. It is a function not only of the gain or loss itself, but also of *Si*, *t* , the value

of the investor's holdings of stock *i* at time *t*, and of a state variable *zi*, *t* , which measures the investor's gains or losses on the stock prior to time *t* as a fraction of *Si*, *t* . By including *Si*, *t* and *zi*, *t* as arguments of v, we allow the investor's prior investment performance to affect the way subsequent losses are experienced. In words, the gain is the value of stock *i* at time *t* + 1 minus its value at time *t* multiplied by the risk-free rate. Expected return lead by one month minus equals to market return minus risk free rate.

4.6 Investor Mental Accounting

Investor Mental Accounting is 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. A stock with a high price–dividend ratio (a growth stock) is 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 (a value stock) has often had dismal prior performance, burning the investor, who now views it as riskier, and requires a higher average return.

The investor 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 is to assess whether mental accounts formed on the basis of the price-divided ratio have any explanatory power on the market reaction. It is to assess whether the companies that pay lower divided are able to beat the high paying divided companies.

Stocks with low price–dividend ratios (dividend yield) have higher average returns than stocks with high price–dividend ratios. Multifactor models that have 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 have a high mean, excess volatility, and are moderately predictable in the time series, while the risk-free rate is constant and low.

4.7 Investor Overconfidence

Investor overconfidence shall be measured using trading volume to ascertain turnover. Turnover rate will be used as a measure of volume of transactions (Adel & Mariem, 2013). The trading volume is measured by turnover as follows:

$$turnover = \frac{nit}{Nit} \quad (4)$$

Where nit is the number of shares traded of stock i (volume traded per month); Nit is the number of exchanges of stock i (number of deals); t is time; i is listed company. Excessive

trading of shares on investor confidence contributes to excessive volatility (Adel & Mariem, 2013).

Table 1: Summary of Measuring Variables

Dependent variable	**Measure**	**Proxy**	**Empirical Review**	**Data**
Stock Market Reaction	(Abnormal Returns)	$AR_{i,t} = R_{i,t} - R_{m,t}$	De Bondt and Thaler (1985)	Past returns
Independent Variables	**Measure**	**Proxy**	**Empirical Review**	**Data**
Investor Herd Behaviour	Return dispersion	$CSAD_{it} = \lvert r_{it} - r_{mt} \rvert$	Thirika and Olweny (2015)	Past returns
Investor Loss Aversion	Utility of gains/ losses	Prior gains and losses $X_{i,t+1} = S_{i,t}R_{i,t+1} - S_{i,t}R_{f,t}$	Barberis and Huang (2001)	Returns
Investor 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)	Barberis and Huang (2001)	Past returns
Investor Overconfidence	Trading volume	Turnover rate $= \frac{n_{it}}{N_{it}}$	Adel and Mariem (2013)	Trading volume and number of deals
Note: CSAD is Cross Section Absolute Deviation				

4.8 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:

$$SMR_{it} = \alpha_{it} + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \mu_{it} \quad (5)$$

Where: SMR_{it} is Stock Market Reactions as measured by Abnormal Returns to determine stock market reaction, X is the investor behaviour variables (Investor Herd Behaviour, Investor Loss Aversion, Investor Mental Accounting and Investor Overconfidence). The variable effect on the stock market to determine if there is overreaction or underreaction 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). $i = 1\ldots 67$ companies listed at the NSE, t = time in years from 2004 to 2016 to determine the effects of investor behavior on stock market reactions.

5. Results and Discussion

Table 1.2: Descriptive Statistics

	Stock Market Reactions	Investor Herd Behavior	Investor Loss Aversion	Investor Mental Accounting	Investor 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 shows 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, investor loss aversion, investor mental accounting variables and only investor 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 Investor 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 Investor 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 Investor 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 Investor 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 reasons 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. Unit root is a formal test of a variable stationarity in time series analysis. A series is said to be (weakly or covariance) stationary if the mean and autocovariances of the series do not depend on time. Any series that is not stationary is said to be non-stationary. The next section tried to diagnose 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.

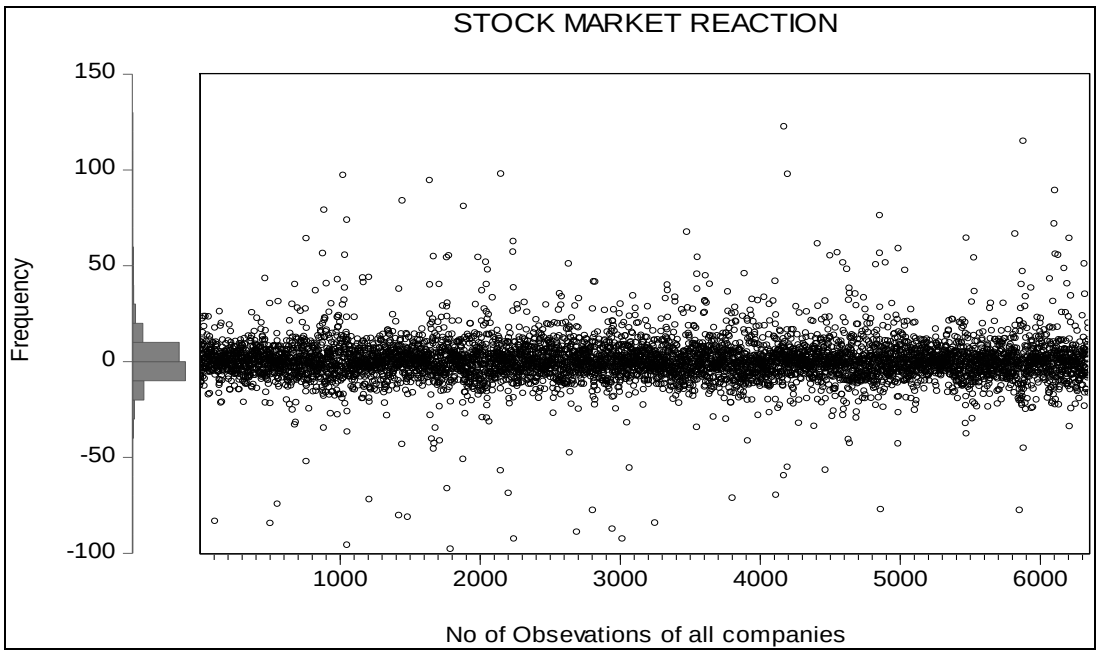

Figure 1: Stock Market Reaction

Figure 1 presents the scatter plots of the stock market reaction of all the 48 companies of the 67 companies used in analysis. The data is composed of 6348 observations. This graph is drawn to skill because of the large observations. The graph shows that the raw data is tightly packed.

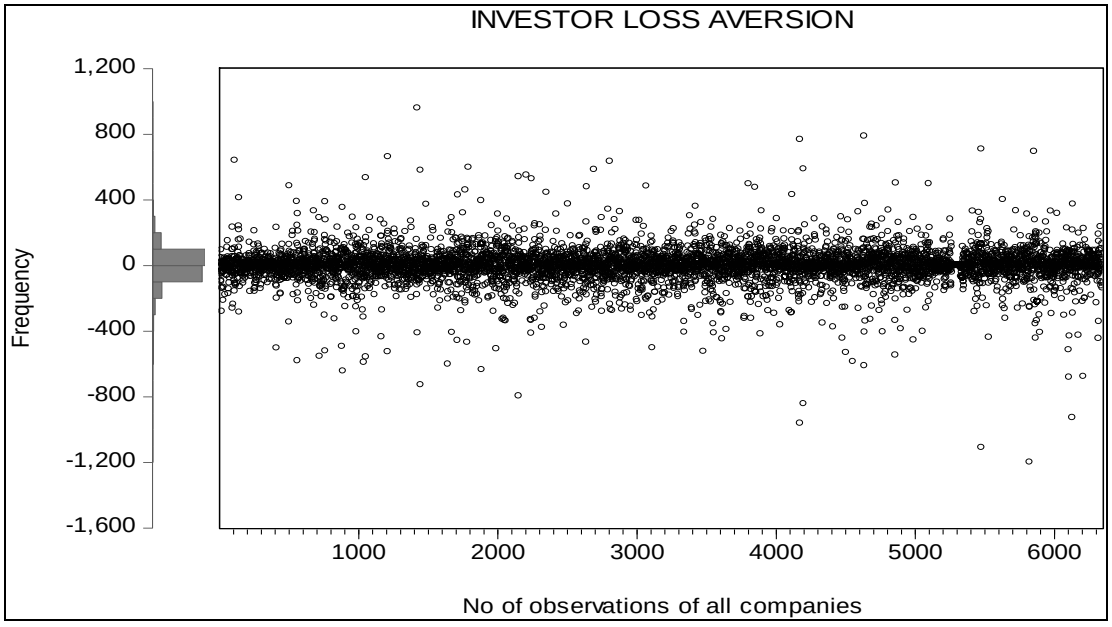

Figure 1.1: Investor Loss Aversion

Figure 1.1 presents the scatter plots of the Investor loss aversion of all the 48 companies of the 67 companies used in analysis. The data is composed of 6348 observations. This graph is drawn to skill because of the large observations. The graph shows that the raw data is tightly packed.

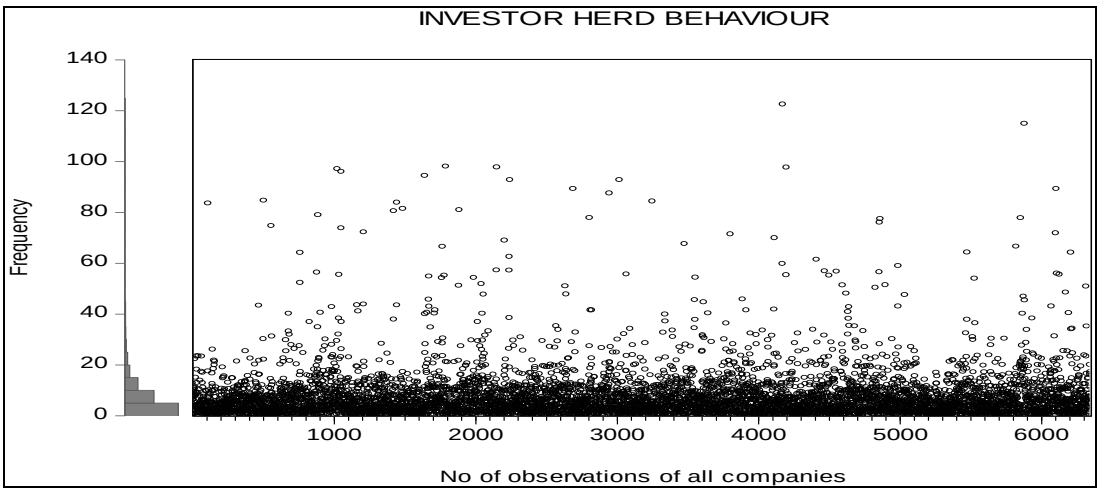

Figure 1.2: Investor herd behaviour

Figure 1.2 presents the scatter plots of the Investor herd behaviour of all the 48 companies of the 67 companies used in analysis. The data is composed of 6348 observations. This graph is drawn to skill because of the large observations. The graph shows that the raw data is tightly packed.

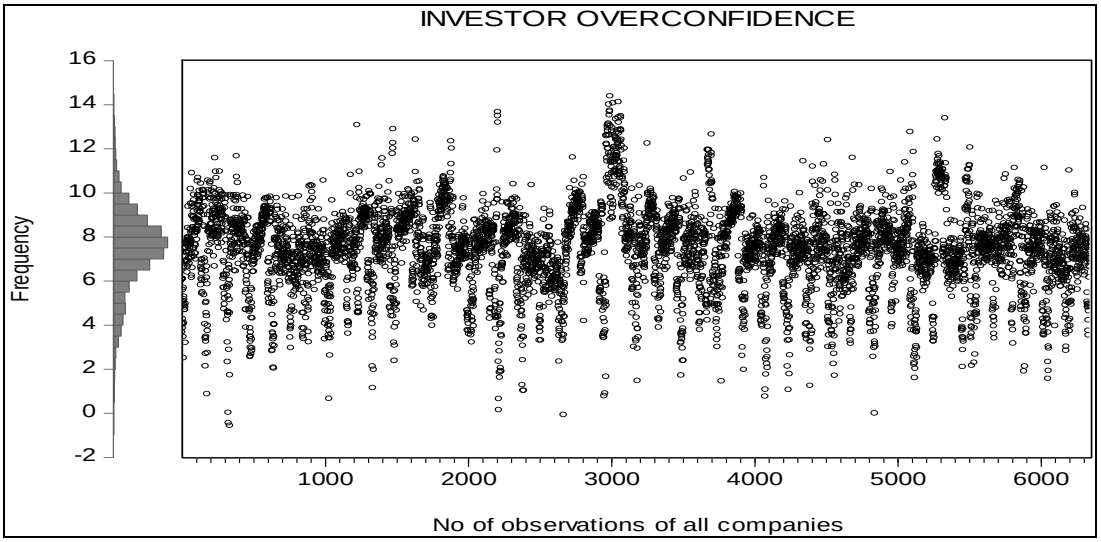

Figure 1.3: Investor overconfidence

Figure 1.3 presents the scatter plots of the Investor overconfidence of all the 48 companies of the 67 companies used in analysis. The data is composed of 6348 observations. This graph is drawn to skill because of the large observations. The graph shows that the raw data is tightly packed.

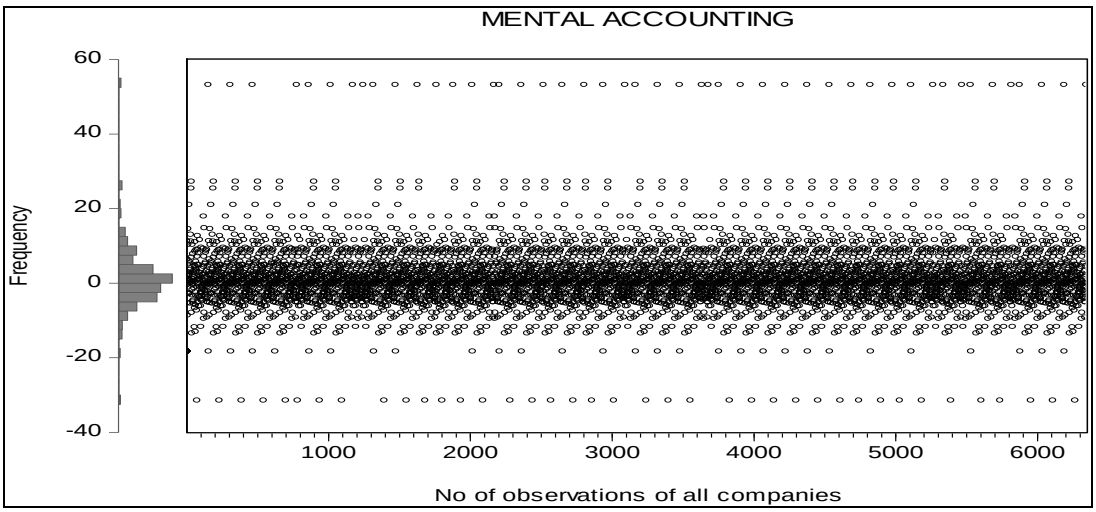

Figure 1.4: Mental accounting

Figure 1.4 presents the scatter plots of the mental accounting of all the 48 companies of the 67 companies used in analysis. The data is composed of 6348 observations. This graph is drawn to skill because of the large observations. The graph shows that the raw data is tightly packed.

5.1 Model Specification Tests

Table 1.2: Stock Market Reaction Unit Root Test

Panel unit root test: Summary				
Series: Stock Market Reaction				
Method	**Statistic**	**P-value**	**Cross-sections**	**Observation**
Null: Unit root (assumes individual unit root process)				
Levin, Lin & Chu t*	-96.0960	0.0000	48	6292
Null: Unit root (assumes common unit root process)				
Im, Pesaran and Shin W-stat	-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

The results from the unit root test for all the cross-sections in the variable stock market reaction in table 1.2 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 tests 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).

5.2 Investor Herd Behaviour Unit Root Test

Table 1.3: Investor Herd Behaviour Unit Root Test

Panel Unit Root Test: Summary				
Series: Investor Herd Behavior				
Method	**Statistic**	**P-value**	**Cross-sections**	**Observation**
Null: Unit root (assumes individual unit root process)				
Levin, Lin & Chu t*	-67.8411	0.0000	48	6295
Null: Unit root (assumes common 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

The results from the unit root test for all the cross-section in table 1.3 above shows that all the 48 cross sections in the investor herd behavior variable 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 considering simultaneously all the cross-section are all stationary for the investor herd behavior 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 tests of stationary 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 investor herd behavior variable was stationary in the two cases of test. In conclusion, the test of stationarity is important because it helps identify the order of integration of a variable and avoid spurious regression. In this case, the investor herd behavior variable is integrated of order zero (0).

5.3 Investor Loss Aversion Unit Root Test

Table 4.4: Investor Loss Aversion Unit Root Test

Panel Unit Root Test: Summary				
Series: Investor Loss Aversion				
Method	**Statistic**	**P-value**	**Cross-sections**	**Observation**
Null: Unit root (assumes individual unit root process)				
Levin, Lin & Chu t*	-94.5903	0.0000	48	6236
Null: Unit root (assumes common 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

The results from the unit root test for all the cross-sections in table 1.4 above shows that all the 48 cross-sections for the investor loss aversion variable 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 considering simultaneously the cross section are all stationary for the investor loss aversion 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 other tests 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 for 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 investor loss aversion variable was stationary in the two cases of test. In conclusion, the test of stationarity is important because it helps to identify the order of integration of a variable and avoid spurious regression. In this case, the investor loss aversion variable is integrated of order zero (0).

5.4 Investor Mental Accounting Unit Root Test

Table 1.5: Investor Mental Accounting Unit Root Test

Panel Unit Root Test: Summary				
Series: Investor Mental Accounting				
Method	**Statistic**	**P-value**	**Cross-sections**	**Observation**
Null: Unit root (assumes individual unit root process)				
Levin, Lin & Chu t*	-91.3319	0.0000	48	6300
Null: Unit root (assumes common 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

The results from the unit root test for all the cross-sections in table 1.5 above shows that all the 48 cross sections for the investor mental accounting variable are 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 in the cross-section are all stationary for the investor mental accounting variable. In other words, they do not have the unit root problem since the null hypothesis of unit root is rejection as depicted by the significant p-value of 0.0000.

The lower section presents yet another three tests 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 investor mental accounting variable was stationary in the two cases of test. In conclusion, the test of stationarity is important because it helps identify the order of

integration of a variable and avoid spurious regression. In this case the investor mental accounting variable is integrated of order zero (0).

5.5 Investor Overconfidence Unit Root Test

Table 1.6: Investor Overconfidence Unit Root Test

Panel Unit Root Test: Summary				
Series: Investor Overconfidence				
Method	**Statistic**	**P-value**	**Cross-sections**	**Observation**
Null: Unit root (assumes individual unit root process)				
Levin, Lin & Chu t*	-9.00532	0.0000	48	6250
Null: Unit root (assumes common 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

The results from the unit root test for all the variables in table 1.6 above shows that all the 48 cross sections of the investor overconfidence variable 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 all stationary for the investor overconfidence variable. In other words, they do not have the unit root problem since the null hypothesis of unit root is rejection as depicted by the significant p-value of 0.0000.

The lower section presents yet another three tests 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 is that the Investor overconfidence variable is stationary in the two cases of test. In conclusion, the test of stationarity is important because it helps to identify the order of integration of a variable and avoid spurious regression. In this case, the investor overconfidence variable is integrated of order zero (0).

5.6 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.

5.7 Investor Herd Behaviour

Table 1.7: Investor Herd Behavior (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	**Statistic**	**Degrees of freedom**	**P-value**
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

Table 1.7 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.

5.8 Investor Loss Aversion

Table 1.8: Investor Loss Aversion (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	**Statistic**	**Degrees of freedom**	**P-value**
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

Table 1.8 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.

5.9 Investor Mental Accounting

Table 1.9: Investor Mental Accounting (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	**Statistic**	**Degrees of freedom**	**P-value**
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

Table 1.9 above presents the results on cross-sectional dependence 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 is 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 to other cross-sections.

5.10 Investor Overconfidence

Table 1.10: Investor Overconfidence (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	**Statistic**	**Degrees of freedom**	**P-value**
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

Table 1.10 above presents the results on cross-sectional dependence 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 give a strong evidence against the null hypothesis. The interpretation is that some information in each of the cross-sections has the tendency to flow to other cross-sections.

5.11 Stock Market Reaction

Table 1.11: Stock Market Reaction (CSDT)

Null hypothesis: No Cross-Section Dependence (Correlation)			
Test	**Statistic**	**Degrees of freedom**	**P-value**
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

Table 1.11 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 in Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD, and it was evident that there is cross-sectional dependence in this variable. The p-value gave a strong evidence against the null hypothesis. The interpretation is that some information in each of the cross-sections tends to flow to other cross-sections.

5.12 Multicollinearity Test / Correlation Test

Table 1.12: Pair-wise Correlation Test

	Stock market reaction	Investor herd behavior	Investor loss aversion	Investor mental accounting	Investor 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

Table 1.12 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. 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.

5.13 Causality Tests

Table 1.13 below 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. 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.

Table 1.13: 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

5.14 Cointegration Test

Table 1.14: Pedroni Cointegration Test

Series: Stock Market Reactions, Investor Herd Behavior, Investor Loss Aversion, Investor Mental Accounting and Investor Overconfidence				
Null Hypothesis: No Cointegration				
	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 1.14 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.

5.15 Regression Results

This section presents the results of the regression of investor behaviour variables on stock market reaction. The section looks at the effect of investor herding behaviour on stock market reaction in Kenya; effect of investor loss aversion on stock market reaction in Kenya; effect of investor mental accounting on stock market reaction in Kenya and effect of investor overconfidence on stock market reaction in Kenya. This were as indicated in chapter one as the objectives and hypotheses of the research.

Table 1.15: Regression Results

Dependent Variable: D (Stock Market Reaction)				
Method: ARDL				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-value**
	Long Run Equation			
Investor herding behavior	-0.007668	0.012539	-0.611483	0.5409
Investor loss aversion	-0.081938	0.001262	-64.90446	0.0000
Investor mental accounting	0.046624	0.013585	3.431909	0.0006
Investor overconfidence	-0.161649	0.057601	-2.806351	0.0050
	Short Run Equation			
Error correction term	-0.955183	0.019617	-48.69086	0.0000
D (Investor herd behavior)	0.008895	0.021210	0.419392	0.6749
D (lnvestor loss aversion)	-0.007500	0.002329	-3.220847	0.0013
D (Investor mental accounting)	-0.018467	0.005243	-3.522325	0.0004
D (Investor overconfidence)	0.173716	0.076641	2.266616	0.0234
c	-0.649702	0.329304	-1.972955	0.0485
@trend	0.018573	0.002610	7.116195	0.0000
Mean dependent variance	-0.024467		S.D. dependent variance	17.92854
S.E. of regression	6.337887		Akaike info criterion	6.486322
Sum squared residual	239406.1		Schwarz criterion	6.850516
Log likelihood	-20091.92		Hannan-Quinn criteria	6.612485

The research adopted 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.

Table 1.15 presents the results on both the long run and short run effect of investor behavior on stock market reaction. The study employed the auto-regressive distributed lags method (ARDL) of model estimation. Shin, Pesaran and Smith (1999) say that this method is easily integrated with the pooled mean group estimator. The pooled mean group estimator constraints the long run parameters to be the same across all individuals while allowing the short-term dynamics to take place in panel data analysis. This estimator is also good in this study since it can handle panels with large time-series relative to the number of individual. The results are also shown in a single table since the estimation procedure employed requires that the error-correction term estimated in the long run step be incorporated in the short run dynamics model. The presentation also allows the researcher to view at a glance the difference between the short run results and long run expectation of parameter convergence.

5.16 Effect of Investor Herd Behaviour on Stock Market Reaction in Kenya

From the regression results in table 1.15 above the long run coefficient of investor herding behavior was found to be -0.007668. This value shows that holding other variables in the model constant, an increase in the investor herd behavior by one unit causes stock market reaction to decrease by a value of -0.007668 units. The negative effect shows that there is an inverse relationship between investor herd behavior and stock market reaction.

The coefficient was also found to be statistically insignificant with a t-statistic value of -0.611483. 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 0.012539 and the p-value was found to be 0.5409. The interpretation was that in Kenya, the investor herd behavior has a statistically insignificant effect on stock market reaction in the long-run horizon. The findings indicate that investor herd behavior has no effect on stock market reactions in Kenya.

From the regression results in table 1.15 above the short run coefficient of investor herding behavior was found to be 0.008895. This value shows that holding other variables in the model constant, an increase in the investor herd behavior by one percent causes the stock market reaction to increase by a value of 0.008895 percent. The positive effect shows that there is a direct positive relationship between investor herd behavior and stock market reaction in the short run which is contrary to the long run situation.

The coefficient was also found to be statistically insignificant with a t-statistic value of 0.419392. The standard error was found 0.021210 and the p-value was found to be 0.6749. The interpretation was that in Kenya, the investor herd behavior may have a statistically insignificant effect on market reaction in the short-run horizon contrary to the long run horizon. However, the variable has some economic influence on stock market reaction that cannot ignored entirely. The other implication is that the investors views the short run horizon differently from the long run. The findings indicate that investor herd behavior has an insignificant effect on stock market reactions in Kenya.

The findings were consistent with Blasco, Corredor and Ferreruela (2012) findings that indicated that herding affects current market volatility but has no impact on implied or future volatility. Imitation trading or herding does not transfer significant volatility effects on option markets but affects stock market dynamics. Thirika and Olweny (2015) results were inconsistent with our findings that indicated a significant positive relationship between the deviation in earning of a security and the squared market returns evidence that herding exists in the NSE. There was a positive insignificant result between market returns and herding. Vieira and Pereira (2015) results were inconsistent with our findings as results did not show any evidence in favour of herd formation during periods of significant change in market returns. The regressions show positive and statistically significant coefficients. All the coefficients are significantly positive, indicating that stock return dispersions increase during periods of large price changes. Lee and Lee (2015) findings were inconsistent because results indicated that by changing the size of agent groups, it was established that the more agents share the same expectations about the tipping point, the higher volatility of the asset price emerges.

Fu (2010) results were inconsistent with the results in this study because it shows that all regressions show that difference between $\beta 1$ and $\beta 2$ is significantly positive based on the t value. Since the values of dependent variables are small, the coefficient value and the differences are also small but still significantly different. Herding is more likely to happen during downward market. Lux (1995) found that speculators follow the crowd. Linde (2012) result shows a negative and statistically significant value of coefficient in finish market which was inconsistent with the results in this study. However, the results indicate that there was no evidence of herding in Sweden, Denmark and Norway which was consistent with the findings in this research. Spyrou (2013) findings reviews more than two decades of empirical and theoretical research that provided a significant insight on investor herding behavior.

Lobão and Serra (2002) results were inconsistent with the results in this research which showed the level of herding is significant in either side of the market, purchases or sales. Results indicated that statistically significance at the 1 percent level; indicates statistically significant at the significance of 5 percent level. Messis and Zepranis (2014) findings were inconsistent with the findings in this study because it depicts the presence of herding over two different periods of time. Large differences are observed among the portfolios regarding the herding periods. The results confirm a linear effect of herding on all volatility measures considered. Stocks exhibiting higher levels of herding or adverse herding will also present higher volatility, and from this point of view, herding can be regarded as an additional risk factor. Results were significant at 5 and 10 per cent level respectively. Hachicha (2010) results show the level of significance of the relation herding/returns remains strong, but it decreases at the individual level. The non-stability of the relation between herding behavior and stock returns is not due to individual level hence consistent with the findings in this study.

5.17 Effect of Investor Loss Aversion on Stock Market Reactions in Kenya

From the regression results in table 1.15 above the long run coefficient of investor loss aversion was found to be -0.081938. 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 a value of 0.081938 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 -64.9044. 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 0.001262 and the p-value was found to be 0.0000. The interpretation was that in Kenya the investor loss aversion has a statistically significant effect on stock market reaction in the long-run horizon. This imply that increase in loss aversion would cause a reduction market reaction.

From the regression results in table 1.15 above the short run coefficient of investor loss aversion was found to be -0.007500. This value shows that holding other variables in the model constant, an increase in the investor loss aversion behavior by one percent causes the stock market reaction to increase by a value of 0.007500 percent. The negative effect shows that there is an inverse relationship between investor loss aversion and stock market reaction in the short run which is contrary to the long run situation.

The coefficient in the short run equation was also found to be statistically significant with a t-statistic value of -3.220847. The standard error was found 0.002329 and the p-value was found to be 0.0013. The interpretation was that in Kenya the Investor loss aversion has a statistically significant effect on market reaction in the short-run horizon as well as in the long run horizon. The other implication is that the investors view the short run horizon to be closely related to the long run. The findings therefore indicate that investor loss aversion influences stock market reaction in Kenya.

Seo, Goldfarb and Barrett (2010) results were consistent with the results in this study as it showed that the degree of gain was significantly and positively related to pleasant feeling, whereas the degree of loss was significantly and negatively related to pleasant feeling. Similarly, the degree of loss was positively and significantly related to unpleasant feeling, and the degree of gain was significantly and negatively related to unpleasant feeling. These findings support those of Genesove and Mayer (2001) who found that investor loss aversion had positive effect on stock market reaction when considered to enter the model linearly and negative when raised to the second power. Harinck, Beest, Dijk and Zeeland (2012) results were consistent with this study because the results showed that loss aversion increases when larger amounts of money are at stake, but especially when people fill in the loss side of the gambles.

Gächter, Johnson and Herrmann (2007) were consistent with this study because the results showed that loss aversion in the riskless choice task and loss aversion in the risky choice task are highly significantly and strongly positively correlated. Brenner, Rottenstreich, Sood and Bilgin (2007) results indicated that PLA is stronger than VLA. Bell and Lattin (2000) results showed that PGAIN and PLOSS are replaced by a single PRICE variable. The author found strong evidence of loss aversion. Bond and Satchell

(2006) results were consistent with this study because the findings showed that when agents are loss averse, there are utility gains or losses are incurred.

Easley and Yang (2015) were inconsistent with results in this study because the findings showed that if loss-averse investors and arbitrageurs only differ in the way of deriving loss aversion utility, then loss-averse investors vanish and have no effect on long run asset prices for an empirically relevant range of parameters. Jarrow and Zhao (2006) results were consistent because it showed significant differences in M-V and M-LPM optimal portfolios. De Bondt and Thaler (1985) were consistent with the findings in this study because results indicate that long-term prior losing stocks on average outperform long term prior winning stocks. Barberis, Huang and Santos (2001) was consistent with the results in this study because the authors developed a framework can help explain the high mean, excess volatility, and predictability of stock returns, as well as their low correlation with consumption growth.

5.18 Effect of Investor Mental Accounting on Stock Market Reaction in Kenya

From the regression results in table 1.15 above the long run coefficient of investor mental accounting was found to be 0.046624. This value shows that holding other variables in the model constant, an increase in the Investor loss aversion by one unit causes the market reaction to increase by a value of 0.046624 percent. The positive effect shows that there is a direct relationship between investor loss aversion and stock market reaction.

The coefficient was also found to be statistically significant with a t-statistic value of 3.431909. 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 0.013585 and the p-value was found to be 0.0006. The interpretation was that in Kenya investor mental accounting has a statistically significant effect on stock market reaction in the long-run. This imply that increase in loss aversion would cause an increase in market reaction

From the regression results in table 1.15 above the short run coefficient of investor mental accounting was found to be -0.018467. This value shows that holding other variables in the model constant, an increase in the investor mental accounting by one percent causes stock market reaction to decrease by a value of 0.018467 percent. The negative effect shows that there is an inverse relationship between investor mental accounting and stock market reaction in the short run which is contrary to the long run situation.

The coefficient in the short run equation was also found to be statistically significant with a t-statistic value of -3.522325. The standard error was found 0.005243 and the p-value was found to be 0.0004. The interpretation was that in Kenya the investor mental accounting has a statistically significant effect on market reaction in the short-run horizon as well as in the long run horizon. The other implication is that the investors views the short run horizon to be differently related to the long run horizon regarding returns on securities. The findings therefore indicate that investor mental accounting has a significant effect on stock market reaction in Kenya.

Barberis and Huang (2001) was consistent with the findings in this study because results showed that there was a substantial value premium in the cross-section, and this premium can to some extent be captured by the same kinds of multifactor models that have been successful in actual data. The author found that investors who are more likely to frame their decisions narrowly would vary with stock characteristics in a predictable manner, those stocks might exhibit greater volatility and lower correlations with other stocks within the same category. The author found that stocks with a low price-dividend ratio have a value stock has often had dismal prior performance, burning the investor, who now views it as riskier, and requires a higher average return. These findings support those of the author who found that the portfolio formed to mimic the effect of mental accounting have 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 to attract investors.

Keim (1985) results were consistent with the findings in this study because dividend yield and stock returns showed coefficient was positive and significant in both January (t = 5.60) and non-January months (t = 3.30), although the sub-period results indicate substantial variation in the magnitude of the coefficients through time. Litzeberger and Ramaswamy (1980) results were consistent with the findings in this study because the results the indicated significant positive coefficients in both ex-months and non-ex-months. Park (2010) results were also consistent and found that dividend-price ratio has significant predictive power for future stock returns. Park (2010) found that dividend-price ratio showed evidence of strong predictive power during one period, while it exhibited weak or no predictive power at other times.

Desari and Huang-Meir (2015) results were consistent with the results in this study because findings indicated that abnormal revisions in the value of a stock are more strongly positively (negatively) associated with future increases (decreases) in dividends when the market valuation of the stock contains more private information that managers can exploit. Kumar and Lim (2008) results suggested that investors' framing choices are likely to have implications for stock returns and found that investors' stock preferences vary systematically with the degree of trade clustering was consistent with this study because findings indicated that the degree of trade clustering is related to investors' stock preferences and portfolio returns.

Lim (2004) results were consistent with the principles of mental accounting (Thaler (1985) according to which individuals attain higher utility by integrating losses and segregating gains which was positive and significant (½ = 0:193, p-value= 0:000), which is consistent with the findings in this study. Lim (2006) results suggested that mental accounting is likely to play a significant role in investors' trading decisions.

Heath, Chatterjee and France (1995) were consistent with the findings in this study because results demonstrated that mental accounting principles, price perception, and reference dependence are sensitive to the ways in which deviations from reference states are framed. Frydman, Hartzmark and Solomon (2015) findings were consistent with this study because results showed that selling an asset and buying another one in quick succession is a way of extending the original investing episode and maintaining the initial

mental account. Thaler and Johson (1990) was consistent with findings in this study because the result indicated that people are risk averse for some gambles when they have a segregated prior loss and risk seeking after segregated prior gain. The findings of this research also support the views of Miller and Modigliani (1961) who argued that divided does not reflect the value of the firm since the management might increase dividend payout just to manipulate the investors into buying more of the firm's shares even when the actual net worth of the firm is not desirable.

5.19 Effect of Investor Overconfidence on Stock Market Reaction in Kenya

From the regression results in table 1.15 above the long run coefficient of Investor overconfidence was found to be -0.161649. This value shows that holding other variables in the model constant, an increase in the Investor overconfidence by one percent causes the market reaction to increase by a value of 0.161649 percent. The negative effect shows that there is a direct relationship between Investor overconfidence and market reaction.

The coefficient was also found to be statistically significant with a t-statistic value of -2.806351. 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 0.057601 and the p-value was found to be 0.0050. The interpretation was that in Kenya the investor overconfidence has a statistically significant effect on market reaction in the long-run horizon. This imply that increase in Investor overconfidence would cause an increase in market reaction.

From the regression results in table 1.15 above the short run coefficient of Investor overconfidence was found to be 0.173716. This value shows that holding other variables in the model constant, an increase in the Investor overconfidence by one percent causes the market reaction to decrease by a value of 0.173716 percent. The negative effect shows that there is an inverse relationship between Investor overconfidence and market reaction in the short run which is contrary to the long run situation.

The coefficient in the short run equation was also found to be statistically significant with a t-statistic value of 2.266616. The standard error was found 0.076641 and the p-value was found to be 0.0234. The interpretation was that in Kenya the Investor overconfidence has a statistically significant effect on market reaction in the short-run horizon as well as in the long run horizon. The other implication is that the investors views the short run horizon to be differently related to the long run horizon regarding returns on securities. The findings therefore indicate that investor overconfidence influences stock market reaction in Kenya.

The findings in this study were consistent with Adel and Mariem (2013) who found that β coefficient has a positive significant level of trading volume market performance in the Tunisia stock exchange. Yeoh and Wood (2011) results were consistent with this study because the findings showed the coefficients for CONF and average transaction values both indicate a significant negative relationship with portfolio performance. Huisman, Sar and Zwinkels (2010) were consistent with results in this study because the findings confirmed that surveyed retail investors exhibit a significant overconfidence bias. Daniel and Titman (1999) findings were inconsistent with the results

in this study because the findings indicated that returns are unrelated to past accounting performance, but strongly negatively related to the component of past returns orthogonal to this publicly available fundamental information. Grinblatt and Keloharju (2009) were consistent with results in this study because the numbers of flat fines are positively and marginally significantly related to log of turnover. Biais, Hilton, Mazurier and Pouget (2005) empirical results show that miscalibration reduces and self-monitoring enhances trading performance which is consistent with the results in this study. Biais, Hilton, Mazurier and Pouget (2005) showed that miscalibration reduces and self-monitoring enhances trading performance.

These findings are consistent those of Metwally and Darwish (2015) where the investor overconfidence had a positive and statistically significant effect on stock market reaction. Tariq and Ullah (2013) was also consistent because they found a positive effect of investor overconfidence on stock market reaction hence consistent with the results in this study. Barber and Odean (1999) documented that men trade 45 percent more than women because the results were consistent with the results in this study because findings indicate trading reduces men's net returns by 2.65 percentage points a year as opposed to 1.72 percentage points for women therefore individual investors lose money, on average, as a result of excessive trading in actual brokerage account data. Barber and Odean (2001) found that men trade more than women and thereby reduce their returns more so than do women.

Daniel, Hirshleifer and Subrahmanyam (1998) result was consistent with the results in this study because findings showed that positive return autocorrelations can be a result of continuing overreaction. Daniel and Titman (2006) was consistent with the results in this study because finding indicated that returns are unrelated to past accounting performance, but strongly negatively related to the component of past returns orthogonal to this publicly available fundamental information. Glaser and Weber (2001) results were not consistent with the findings in this study because the results did not find significant correlations between the monthly gross return in our 51-month period and our overconfidence measures. Glaser, Langer and Weber (2003) showed that overconfidence is a pervasive bias among market participants including professional investors.

Jlassi et al (2013) GARCH effect is consistent with this study because results show positive and highly significant at the 1% level on statistical analysis of market return and trading volume series provides insights that the behavior of indices in global market exhibits an extreme and abnormal high volatility. Zaiane and Aboub (2009) result was consistent with the findings in this study because results showed a positive and significant contemporaneous association between volume and volatility. Boussadi (2013) results was consistent with the findings in this study because results indicated that the sum of the lagged coefficients associated to turnover is positive and significant. Ko and Huang (2001) result was consistent with the findings in this study because results confound the positive relationship between overreaction and overconfidence. Statman et al (2006) result was consistent with results in this study because findings showed positive and highly significant association between market turnover and lagged market returns.

5.20 Error Correction Term and Trend

From the regression results in Table 1.15 the other two key statistics were on error correction and the trend. The error correction term had a coefficient of -0.955183. This value as it name suggest is the speed at which the model is correcting toward the equilibrium. In other word is the speed at which the disequilibrium is being eliminated from the model. The value shows that the model is above equilibrium and is correcting at the rate of 95%. This implies that since our data is on monthly frequency, 95% of the discrepancy in the previous month is being corrected in the current month. The coefficient is also statistically significant with a p-value of 0.0000 and a t-statistic of -48.69086.

The other key issue was the inclusion of trend in the model. The notion of including the trend was motivated by an attempt to capture any trend that was in the variables included in the model. The coefficient had a value of 0.018573. It was also established that this coefficient was also statistically significant with a t-statistic of 7.116195 and a p-value of 0.0000.

5.21 Post Estimation Tests

Table 1.16: Model Residuals Unit Root Test

Residuals Unit Root Test	Statistic	P-value	Cross-sections	Observations
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-87.9036	0.0000	48	6202
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-79.9100	0.0000	48	6202
ADF - Fisher Chi-square	3509.55	0.0000	48	6202
PP - Fisher Chi-square	3546.38	0.0000	48	6204

Table 1.16 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. There is also a graph showing the distribution of residuals for each company see (appendix iv) for details.

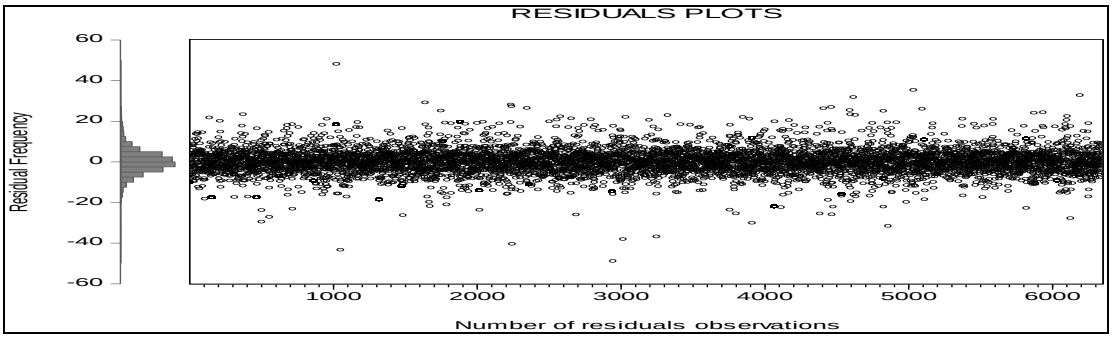

Figure 4.6: Residuals plots

Figure 4.6 presents the plots of the residuals from regression analysis. The plot shows that the residuals are evenly distributed around the zero line. The interpretation is that the model is identified with high precision. Another interpretation is that the negative effects and positive effects of the residuals' councils out and thus the model is identified with high precision.

5.22 Confidence Interval for Coefficients

Table 1.17: Coefficients Confidence Interval

Coefficient Confidence Intervals			
		95% Confidence Interval	
Independent Variable	**Coefficient**	**Low**	**High**
Investor Herd Behavior	-0.007668	-0.032250	0.016914
Investor Loss Aversion	-0.081938	-0.084413	-0.079464
Investor Mental Accounting	0.046624	0.019991	0.073256
Investor Overconfidence	-0.161649	-0.274568	-0.048730

Table 1.17 presents the results on the confidence interval of the coefficients. From the finding all the coefficients fell within the confidence intervals. The low and high limits give the bound of confidence. The interpretation is that the model was stable.

5.23 Hypothesis Test of Rationality

H01: Investor herd behaviour has no significant effect on stock market reaction in Kenya.

Table 1.18 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic -0.611483, F-statistic 0.373912 and Chi-square 0.373912. These values are statistically insignificant as showed by p-values of 0.5409, 0.5409 and 0.5409 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 1.18: Investor herd behaviour has no significant effect on stock market reaction in Kenya

Wald Test:			
Test Statistic	**Value**	**Degrees of freedom**	**Probability**
t-statistic	-0.611483	5960	0.5409
F-statistic	0.373912	(1, 5960)	0.5409
Chi-square	0.373912	1	0.5409
Null Hypothesis: C(1)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(1)		-0.007668	0.012539
Restrictions are linear in coefficients.			

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

Table 1.19: Investor loss aversion has no significant effect on stock market reactions in Kenya

Wald Test:			
Test Statistic	**Value**	**df**	**Probability**
t-statistic	-64.90446	5960	0.0000
F-statistic	4212.589	(1, 5960)	0.0000
Chi-square	4212.589	1	0.0000
Null Hypothesis: C(2)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		**Value**	**Std. Err.**
C(2)		-0.081938	0.001262
Restrictions are linear in coefficients.			

Table 1.19 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic -64.90446, F-statistic 4212.589 and Chi-square 4212.589. 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.

H_{03}: Investor mental accounting has no significant effect on stock market reactions in Kenya.

Table 1.20 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic 3.431909, F-statistic 11.77800 and Chi-square 11.77800. These values are statistically significant as showed by p-values of 0.0006, 0.0006 and 0.0006 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 word investor mental accounting contribute very significantly to the stock market reaction.

Table 1.20: Investor mental accounting has no significant effect on stock market reactions in Kenya

Wald Test:			
Test Statistic	**Value**	**Degrees of freedom**	**Probability**
t-statistic	3.431909	5960	0.0006
F-statistic	11.77800	(1, 5960)	0.0006
Chi-square	11.77800	1	0.0006
Null Hypothesis: C(3)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		**Value**	**Std. Err.**
C(3)		0.046624	0.013585
Restrictions are linear in coefficients.			

5.24 Investor overconfidence has no significant effect on stock market reactions of listed companies in Kenya

Table 1.21: 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	-2.806351	5960	0.0050
F-statistic	7.875605	(1, 5960)	0.0050
Chi-square	7.875605	1	0.0050
Null Hypothesis: C(4)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		**Value**	**Std. Err.**
C(4)		-0.161649	0.057601
Restrictions are linear in coefficients.			

Table 1.21 presents the results for the ward test of hypothesis one. The three test statistics are t-statistic -2.806351, F-statistic 7.875605 and Chi-square 7.875605. These values are statistically significant as showed by p-values of respectively 0.0050, 0.0050 and 0.0050. 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.

6. Conclusion

The study concluded that in the NSE, Kenyan stock market, the investor herd behavior has a no significant effect on stock market efficiency. 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.

This variable was only significant in only one of the five regressions that were ran to reveal the dynamics of the effect of investor behavior on market reaction. This shows that investors may remain silent at times and withhold trading even when the other investors are sharing information that might trigger trading. In extension, though this variable has a statistically insignificant effect it should be retained since statistical significance and economic significance are different.

The study concludes that in Kenyan stock market, the investor 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.

This variable was significant in all the five regressions that were ran to reveal the dynamics of the effect of the investor loss aversion on market reaction. This showed that investors are concerned about the losses or gains in their investment decisions in Kenya which results in stock market reactions.

The study concluded that in Kenyan stock market, the investor 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.

This variable was significant in all the five regressions that were ran to reveal the dynamics of the effect of the investor mental accounting on stock market reaction. This showed that investors are concerned about the divided announcement by the listed companies and that they are likely to make investment decisions in securities in Kenya based on divided information.

The study concluded that in Kenyan stock market, investor 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.

This variable was statistically significant in all the five regressions that were ran to reveal the dynamics of the effect of the investor overconfidence on stock market reaction. This shows that investors are likely to purchase more stocks in the market when they are overconfident. Overconfidence therefore causes stock market reaction in Kenya.

7. Recommendation

7.1 Investor Herd Behaviour and Stock Market Reactions in Kenya

The investors and stock brokers should be keen on the investor mental accounting bias in the market. The investor bias could lead to stock prices moving from its fundamental values causing abnormal returns hence stock market reaction resulting from to variations in returns. The investors and stock brokers should be keen on investor herd behavior in the market. In this research, it has been revealed that herd behavior has an insignificant effect on stock market reaction. However, these key players should not ignore the investor herd behaviour in the market. Though insignificant, this variable still could have some negative effect on returns and prices of stocks in the market. The study also recommends that CMA (Capital Market Authority) should be keen on malpractices that may cause information asymmetry in the market on securities prices in the market. The regulator should ensure that the trading activities are disclosed to the market players to ensure that investors make informed decisions when deciding on the investment strategies investing. CMA and the NSE should work to improve the modelling of stock prices so as to be able to reflect the information flow and factor in some behavioural

factors that may be significant in influencing returns in the market. This will have the effect of increasing transparency and confidence in the market hence attracting more investors and surely more capital flows into the capital markets.

7.2 Investor Loss Aversion and Stock Market Reactions in Kenya

The investors and stock brokers should be keen on the investor loss aversion bias in the market. The investor bias could lead to stock prices moving from its fundamental values causing abnormal returns hence stock market reaction resulting from to variations in returns. In this research, it has been revealed that investor loss aversion has a significant effect on stock market reaction. It was noted that the investor loss aversion has significant effect on reaction which meant that it leads to the fluctuation of abnormal returns in the market. Since the influence of loss aversion was supported by all the results from the different models to be statistically significant, it would be of help to the investors and stock brokers to consider this variable when tracking the prices of securities.

CMA and the NSE should work to improve the modelling of stock prices so as to be able to reflect the information flow and factor in some behavioural factors that may be significant in influencing returns in the market. This will have the effect of increasing transparency and confidence in the market hence attracting more investors and surely more capital flows into the capital markets.

7.3 Investor Mental Accounting and Stock Market Reactions in Kenya

The investors and stock brokers should be keen on the investor mental accounting bias in the market. The investor bias could lead to stock prices moving from its fundamental values causing abnormal returns hence stock market reaction resulting from to variations in returns. In this research, it has been revealed that investor mental accounting has a significant effect on market reaction. It was noted that the investor mental accounting has significant effect on stock market reaction which meant that it leads to the fluctuation of abnormal returns in the market. Since the influence of investor mental accounting was supported by all the results from the different models to be statistically significant, it would be of help to the investors and stock brokers to consider this variable when tracking the prices of securities.

CMA and the NSE should work to improve the modelling of stock prices so as to be able to reflect the information flow and factor in some behavioural factors that may be significant in influencing returns in the market. This will have the effect of increasing transparency and confidence in the market hence attracting more investors and cause more capital flows into the capital markets.

7.4 Investor Overconfidence and Stock Market Reactions in Kenya

The investors and stock brokers should be keen on the investor overconfidence in the bias in the market. The investor bias could lead to stock prices moving from its fundamental values causing abnormal returns hence stock market reaction resulting from to variations in returns. In this research, it has been revealed that investor overconfidence has a significant effect on market reaction. It was noted that the investor overconfidence has

significant effect on stock market reaction which meant that it lead to the fluctuation of abnormal returns in the market. Since the influence of investor overconfidence was supported by all the results from the different models to be statistically significant, it would be of help to the investors and stock brokers to consider this variable when tracking the prices of securities.

CMA and the NSE should work to improve the modelling of stock prices so as to be able to reflect the information flow and factor in all behavioural factors that may be significant in influencing returns in the market. This will have the effect of increasing transparency and confidence in the market hence attracting more investors and cause more capital flows into the capital markets.

7.5 Area for further research

The study maps our previously studied variable of pricing error into the observable measures of mispricing and price overreaction. Prices react to investor behaviour in our model because investors herd, practice mental accounting, are loss averse and overconfident. This research was not able to identify conclusively all the possible variables with explanation power on stocks pricing in Kenya. This was evident from the FMLOS and DOLS models that showed that the model tried to explain approximately 57% to 72% on the variation of the stock market reaction. It is therefore in this light that the future researchers are encouraged to consider other investor behavior biases that are deemed to cause stock market reaction which would increase the predictive capability of the model. Event study to analyze the change in expected and actual earnings. Neuroeconomics research on brain activity of economics and behavioral psychology to study how the brain affects financial decisions should also be the next area of further research. Effects of Social Economic and Political changes in a country on Investor Behaviour and How Macro-Economic Factors affect Stock Pricing Models in NSE should be studied.

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