

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG, SOUTH AFRICA

**INVESTOR REACTION AND SEASONALITY
IN TWO OF AFRICA'S LARGEST EQUITY MARKETS**

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A Dissertation submitted to the Faculty of Law, Commerce and Management, University of the Witwatersrand, Johannesburg in partial fulfilment of the requirements of the degree of Doctor of Philosophy.

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ABSTRACT

The study investigates the overreaction effect and associated January seasonality on the Nigerian Stock Exchange (NSE), a pioneer study. Both anomalies are also investigated on the Johannesburg Stock Exchange (JSE) for persistence. The study finds evidence of overreaction and seasonality on the NSE, in contrast to past studies that find it to be weak-form efficient. The observed overreaction effect on the NSE was accompanied by a January effect. Monthly seasonality was also found on the NSE in the calendar month of June – a “June Effect”; confirming earlier findings on the NSE. For the JSE, the study does not find evidence of overreaction. This implies the overreaction effect can be arbitrated away over time. Although, a mild January effect is evidenced on the JSE, it is only marginally significant, and partly supporting the notion of possible arbitraging away of anomalies with the passage of time and increased relative efficiency. A strong “October effect” was found on the JSE, however. As this is the first documented overreaction effect on the NSE, the evidence from the JSE suggests these anomalies are likely to be arbitrated away in the Nigerian equity market over time as well. This would be an area for future research. In regard of the supposed congruity of return and investor sentiment, only the NSE shows evidence of this. The study finds that when there is an overreaction effect on a bourse, there is a similar trend – albeit in absolute terms – observed with respect to investor sentiment represented by the share turnover ratio.

DECLARATION

I declare that this research report is my own, unaided work. It is being submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree, or examination, in any other university.

.....
Rafiq Raji

..... Day of February 2015.

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1. INTRODUCTION

1.1 Background

Fama (1970) posits that security prices reflect all available relevant information and that as such it would be impossible for any investor to consistently beat the market and consistently generate abnormal returns (Efficient Market Hypothesis (EMH)). The works of De Bondt and Thaler (1985), Fama and French (1988), Lo and MacKinlay (1988), Jegadeesh (1990), Jegadeesh and Titman (1993) and many others, raise questions about this position. To this day, the debate still rages on about market efficiency with two increasingly distinct schools of thought emerging: Traditional finance (proponents of the EMH) and Behavioural Finance.

De Bondt and Thaler (1985) highlight how contrarian investment strategies consistently generate alpha across three to five year time horizons, an occurrence at variance with the EMH. This seminal work on “investor overreaction” or the “winner-loser effect” showed a preponderance of the excess return performance occurring in January, especially for the “loser” or contrarian portfolios. Small-cap firms were also found to outperform large-cap ones thereby raising the question of whether the winner-loser effect wasn’t just another instance of the “size-effect” extensively studied by Banz (1981), Reinganum (1981), Schwert (1983), et cetera. Similar arguments have been raised for the seasonality in the return reversals for winner and loser portfolios especially in the calendar month of January, that is, a “January effect” or “Turn-of-the-year effect” and whether this couldn’t be explained to be as a result of tax-loss selling by investors in consonance with observations by Reinganum (1983), Schultz (1985), et cetera, *ex post* the seminal discovery of that calendar anomaly by Rozeff and Kinney (1976). Apart from showing better return performance, the observed biases were also more prevalent for contrarian portfolios.

In a subsequent study, De Bondt and Thaler (1987) attempted to offer explanations for the numerous arguments spurred by their earlier work. They were not however convincing at explaining the observed seasonality of the excess return performance recorded for the winner

and loser portfolios. In fact, “many puzzles remain, especially regarding the seasonality in excess returns” (De Bondt and Thaler, 1987:579).

Most of the subsequent literature regarding overreaction have had more of an empirical than theoretical focus and yet evidence of seasonality pervades these studies, a preponderance of which are for Non-U.S markets – Australia (Gaunt, 2000), G-7 Countries (Baytas and Cakici, 1999), Asia (McInish, Ding, Pyun, and Wongchoti, 2008), China (Kang, Liu, and Ni, 2002), South Africa (Cubbin, Eidne, Firer, and Gilbert, 2006), Turkey (Bildik and Gulay, 2007), Tunisia (Dhouib and Abaoub, 2007), et cetera. Thus, while seasonality continues to be a recurring observation in overreaction studies, an explanation for its occurrence has not enjoyed as much attention and/or success. They are important nonetheless as robust out-of-sample confirmation of the overreaction hypothesis across geographies and time periods.

Past attempts at explaining the seasonal anomaly include the tax-loss selling (Chan, 1986; D’mello, Fernis, and Hwang, 2003), “window-dressing” by institutional investors (Lakonishok, Shleifer, Thaler, and Vishny, 1991), “data-snooping” (Lo and Mackinlay, 1990; Sullivan, Timmerman, and White, 1999) and “parking the proceeds” (Ritter, 1988) hypotheses. There is also a seeming consensus that the January effect is largely a small-firm phenomenon (Lakonishok and Smidt, 1988; Ritter, 1988; Haug and Hirschey, 2006). A later effort (Haug and Hirschey, 2006) at explaining the turn-of-the year effect suggests that an exhaustive explanation for the January effect remains elusive still since its first discovery by Rozeff and Kinney (1976).

What seems to be consistent in the literature are: buying pressure in January is biased towards undervalued stocks in the prior December, tax-loss selling – though not an exhaustive explanation – seem a motivation for some investors to sell losing stocks in December in markets such as the United States (Schultz, 1985) – even though Reinganum (1983), and Haug and Hirschey (2006) refute this – and for other reasons in some (Kato and Schallheim, 1985; Berges, McConnell, and Schlarbaum, 1984). Tax-loss selling doesn’t explain, however, the subsequent

buying activity in January. Other alternative explanations (Lakonishok et al., 1991; Lo and MacKinlay, 1990; Sullivan et al., 1999; et cetera) have not been found to be exhaustive either since the January effect continues to persist irrespective of investor type or any supposed statistical bias. Additionally, the observed seasonality in winner-loser portfolios with loser stocks or hitherto undervalued stocks earning significant positive risk-adjusted returns in January (De Bondt and Thaler, 1985; Jegadeesh, 1990; et cetera) continues to be unexplained by existing theory (De Bondt and Thaler, 1987).

1.1.1 Efficiency Studies and return trends on the Nigerian Stock Exchange

For the Nigerian equity market, the existing evidence (Ayadi, 1984; Olowe, 1999; Tijjani, Power, and Fifield, 2009; Okpara, 2010; et cetera) suggests it is weak-form efficient. Methodologies of these studies, however, were largely autocorrelation tests. Thus, there is a dearth of studies of trading-rule efficiency tests like that used for this study. Other drawbacks in these prior studies include small sample sizes – Olowe (1999) used fifty-nine (59) randomly selected securities as its sample and Tijjani et al. (2009) used sixty-nine (69). Additionally, they do not include observations beyond the year 2006, a period for which the Nigerian bourse experienced marked activity, and thus the start of a relatively higher level (frequency) of market activity.

In the context of efficiency of markets, residual returns of loser and winner portfolios on the NSE are mapped. And as is evident in Figure 1, there is cursory evidence of loser portfolio returns behaving differently than winner portfolio returns in ways that warrant deeper analysis. Similarly, Figure 2 shows a markedly different pattern for loser portfolio returns than the winner portfolio return pattern in the JSE. The differential portfolio return patterns in these two distinct major equity markets of Africa, point to a compelling need to explore in depth the issues of anomalies such as overreaction and seasonality of returns in these increasingly important regional markets.

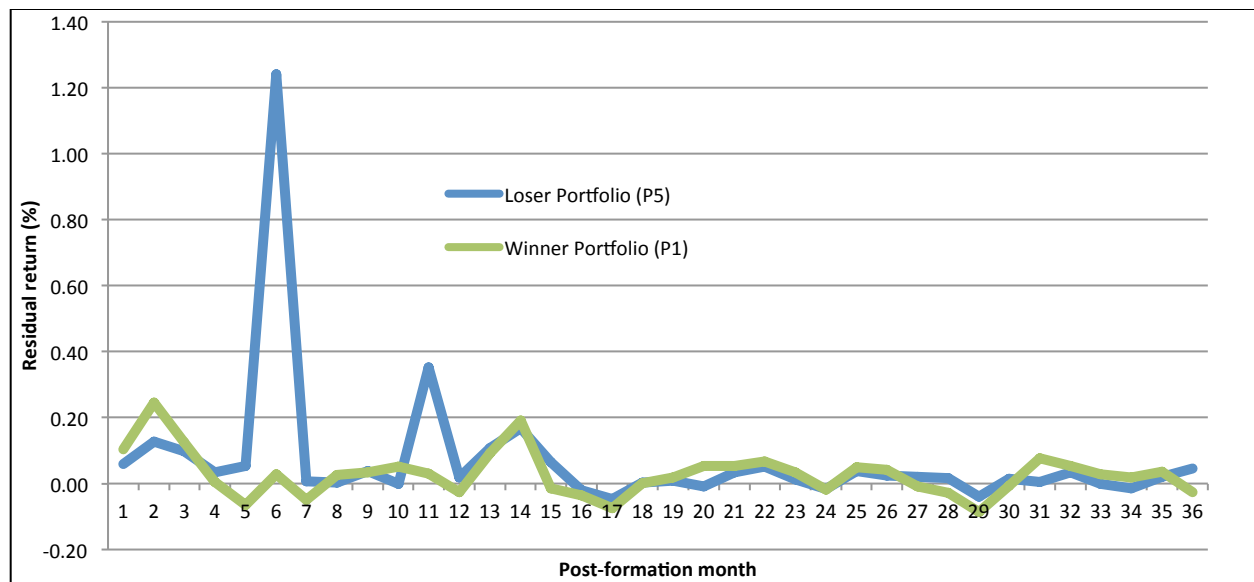


Figure 1: Residual returns for Loser & Winner Portfolios for NSE-listed stocks (1-36 months into the test period between January 2005 and December 2011)

1.1.2 Efficiency Studies and return trends on the Johannesburg Stock Exchange

Evidence of investor overreaction on the Johannesburg Stock Exchange (JSE) (Page and Way, 1992; Muller, 1999; Cubbin, Eidne, Firer and Gilbert, 2006; Venter, 2009; Hsieh and Hodnett, 2011) has been relatively consistent. Findings on the efficiency of the JSE (Gilbertson and Roux, 1977; Strebel, 1987; Knight and Affleck-Graves, 1985; Thompson and Ward, 1995; Philpott and Firer, 1995) and the January effect (Bradfield, 1990; Robins, Sandler, and Durand, 1999; Auret and Cline, 2011), however, remain mixed. It is possible that this is due to study period differences since the highlighted studies used data for different periods – Page and Way (1992) and Cubbin et al. (2006) used data for the period 1974 – 1989 and 1983 – 2005, respectively.

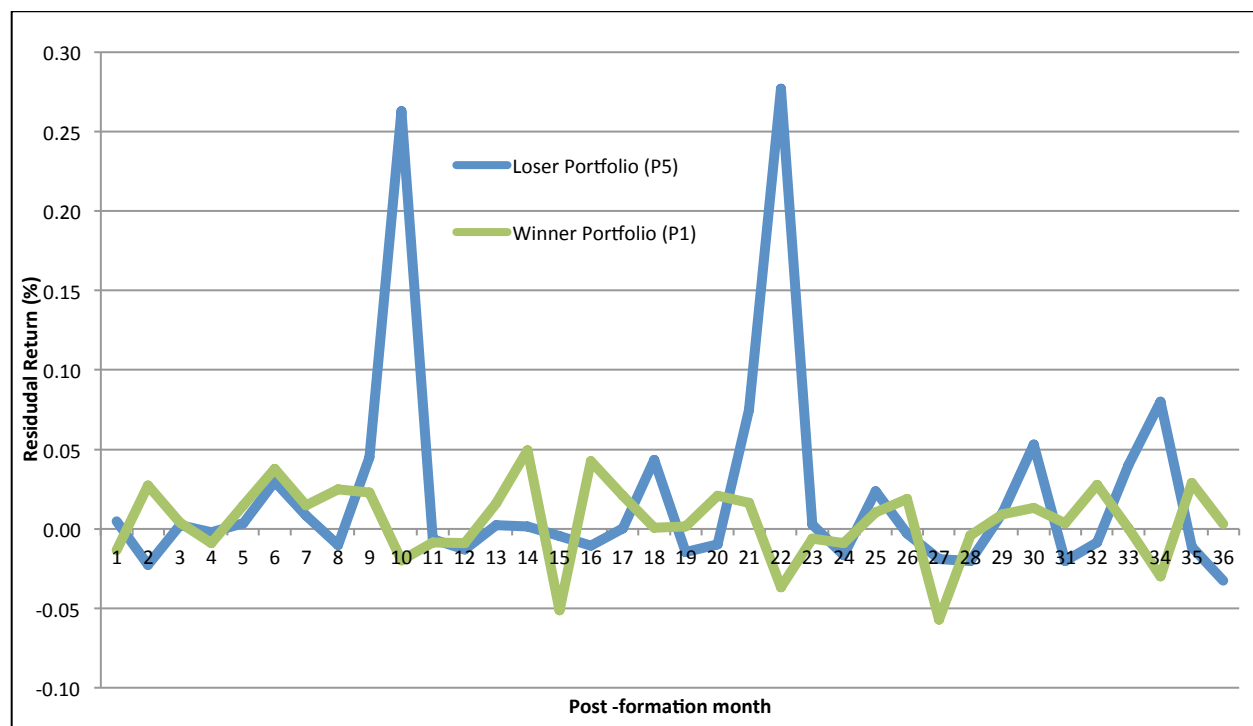


Figure 2: Residual returns for Loser & Winner Portfolios for JSE-listed stocks (1-36 months into the test period between January 2005 and December 2011)

1.2 Purpose of the study

The purpose of this research is to investigate the relationship between investor overreaction and seasonality – the January effect in particular, for which an explanation has remained elusive thus far. The intuition that is investigated is as follows. The losing streak of loser stocks in a prior period is spurred by pessimism (negative investor sentiment) as suggested by [DeBondt and Thaler \(1985\)](#); disequilibria that then persist for varied periods up until the turn of the year. Subsequently, optimism (positive investor sentiment) around the New Year lead investors to take a chance on these supposed “losers,” as evidenced by their positive risk-adjusted return performance in the calendar month of January. If an investor sentiment measure is found to behave in this way in relation to loser returns, it would form the basis for generalizations about the Overreaction and January effects around investor sentiment.

[Baker and Wurgler \(2006\)](#) define investor sentiment as “optimism and pessimism about stocks in general” (p. 1649); and use share turnover as one of their proxies for investor sentiment. Other proxies that have been used are “closed-end fund discount, the number and average first-day returns on Initial Public Offerings (IPOs), the equity shares in new issues, and the dividend premium” ([Baker and Wurgler, 2006:1655](#)). Share turnover has also been found to be seasonal. [Eleswarapu and Reinganum \(1993\)](#) use share turnover as a proxy for liquidity and present evidence showing the “liquidity premium is reliably positive only during the month of January” (p. 385). [Lee and Swaminathan \(2000\)](#) also present evidence showing underreaction and overreaction are linked by trading volume proxied by the turnover ratio (defined as the daily ratio of traded shares to the number of shares outstanding for each stock). Additionally, [Campbell et al. \(1993\)](#) and [Blume et al. \(1994\)](#) provide theoretical evidence that shows strong linkages between stock returns and trading volume. [Al-Khazali \(2014\)](#) also asserts investor sentiment is germane to the return process. Further to these insights, this study uses share turnover as a proxy for investor sentiment.

1.3 Empirical Scope

This study is conducted using data from two of Africa's largest bourses: the Johannesburg Stock Exchange (JSE) and the Nigerian Stock Exchange (NSE). There is evidence that the JSE overreacts (Page and Way, 1992; Cubbin et al., 2006; etc.). For the Nigerian equity market, however, an empirical study to determine if it overreacts, with the tandem January effect, as has been determined for other equity markets, United States (De Bondt and Thaler, 1985, 1987) including South Africa (Page and Way, 1992; Cubbin et al., 2006), is yet to be conducted.

1.3.1 The Johannesburg Stock Exchange

Established in 1887, the Johannesburg Stock Exchange (JSE) is the oldest and most advanced bourse on the African continent. The bourse has since grown from a market capitalization of 51 billion South African Rand (ZAR 51bn) in 1978 to almost 11 trillion South African Rand (equivalent of US\$ 1 trillion) in 2013; accordingly Figure 3 maps the performance of the JSE All Share index for the period 2002-2011. It was just half of its 2013 size in 2009 at 6 trillion South African Rand (ZAR 6 trillion). As at the end of 2013, there were 327 companies listed on the JSE. According to the World Federation of Exchanges (WFE) statistics, the JSE ranked 19th by market capitalization, 26th by liquidity, and 22nd by market turnover; all globally in 2013. Participants on the JSE have access to bid and offer prices, can continuously trade electronically and prices are disclosed in real time. Thus, the JSE is a model African bourse.

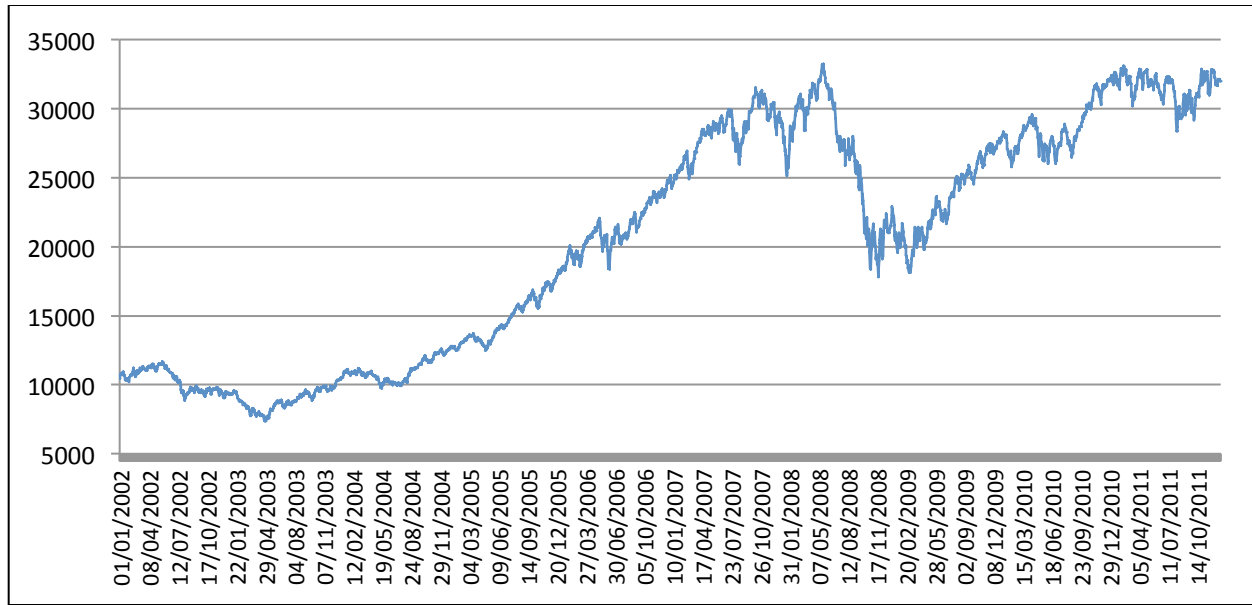


Figure 3: Johannesburg Stock Exchange (JSE) All Share Index (ASI) for the years 2002-11

1.3.2 The Nigerian Stock Exchange

The Nigerian Stock Exchange (NSE) was established in 1960. According to its 2012 annual reports, the NSE had an end-2012 market capitalization of 8.98 trillion Nigerian Naira (NGN 8.98 trillion) or 57.77 billion United States Dollars (USD 57.77 billion) with an average daily turnover for equities of NGN2.65 billion (USD 17.05 million). As in Figure 3 above, representing trends in the JSE, Figure 4 paints a picture of the NSE All Share index performance for the same period of 2002 to 2011. From trades totalling NGN 4.4 million by value in 1962, NGN 658.2 billion worth of trades were executed on the NSE in 2012. Number of listed equities on the NSE has varied between 131 in 1990 to 201 in 2011. The NSE has a trading limit up/limit down threshold for listed equities of 5%. Upon the introduction of primary market making in September 2012, stocks with primary market makers had their limit up/limit down threshold increased to 10%.

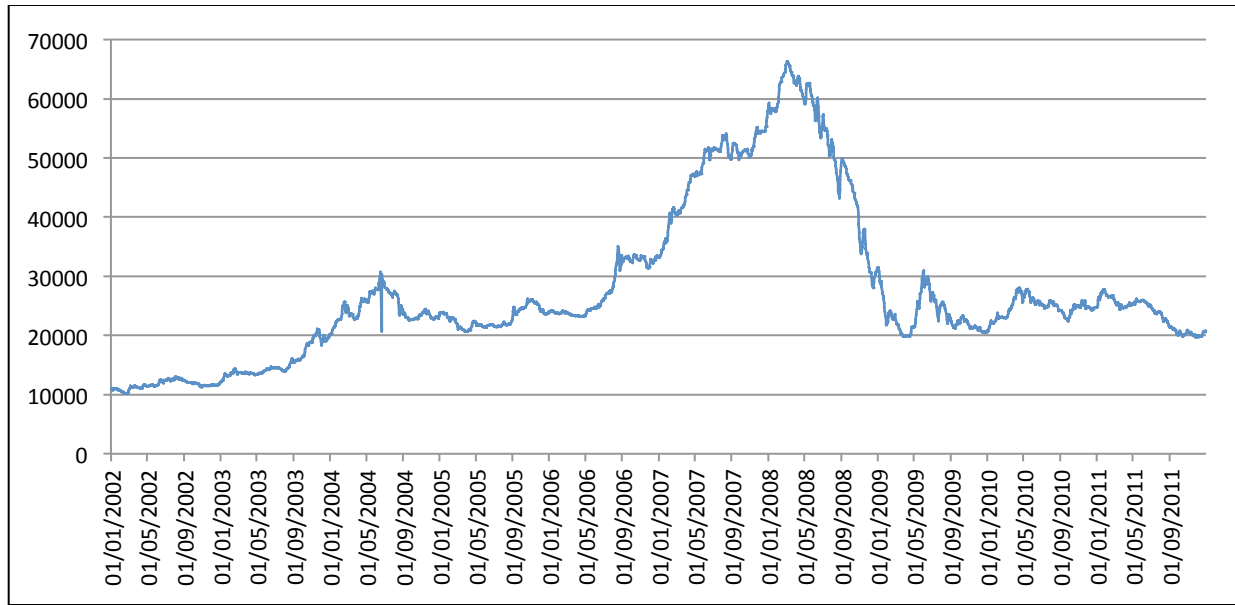


Figure 4: Nigeria Stock Exchange (NSE) All Share Index (ASI) for the years 2002-11

The apparent differences between these two major African bourses are another important motivation for this study; that is, could some salient differences between these markets explain empirical differences documented about the examined market return anomalies? It could be that the relative levels of efficiency of equity markets reflect the overreaction and seasonality phenomena differently; and such differential findings could assist authorities in Nigeria fashion a much more informed reform and growth agenda for their market.

1.4 Hypotheses

The null hypotheses for the statistical tests of the study are as follows:

1. H_01 : As markets are efficient, there is no investor overreaction effect on the NSE. Thus, loser portfolios do not outperform winner portfolios on the NSE.
2. H_02 : As markets are efficient, there is no investor overreaction effect on the JSE. Thus, loser portfolios do not outperform winner portfolios on the JSE.
3. H_03 : As markets are efficient, there is no January effect (or other seasonality) on the NSE. Thus, portfolio returns for the month of January (or any other calendar month) are not different from those of other calendar months on the NSE.
4. H_04 : As markets are efficient, there is no January effect (or other seasonality) on the JSE. Thus, portfolio returns for the month of January (or any other calendar month) are not different from those of other calendar months on the JSE.
5. H_05 : As markets are efficient and investor sentiment behaves similarly as return, investor sentiment is the same irrespective of portfolio or calendar month.

1.5 Significance of the study

This is the first overreaction study for the Nigerian equity market. In light of the significant interest in emerging and frontier markets like the South African and Nigerian equity markets, the findings of this study should find a huge audience amongst global portfolio managers. Also, the overreaction and seasonal anomalies are amongst the few return dependencies that have endured arbitrage and continue to persist.

The study finds evidence of overreaction and seasonality on the NSE, in contrast to past studies that find it to be weak-form efficient. The observed overreaction effect on the NSE was accompanied by a January effect. Monthly seasonality was also found on the NSE in the calendar month of June – a “June Effect”; confirming earlier findings on the NSE. For the JSE, the study does not find evidence of overreaction. This implies the overreaction effect may have been arbitrated away over time. Although, a mild January effect is evidenced on the JSE, it is only marginally significant, and partly supporting the notion of possible arbitraging away of anomalies with the passage of time and increased relative efficiency. A strong “October effect” was found on the JSE, however.

As this is the first documented overreaction effect on the NSE, the evidence from the JSE suggests these anomalies are likely to be arbitrated away in the Nigerian equity market over time as well. This would be an area for future research. In regard of the supposed congruity of return and investor sentiment, only the NSE shows evidence of this. The study finds that when there is an overreaction effect on a bourse, there is a similar trend – albeit in absolute terms – observed with respect to investor sentiment represented by the share turnover ratio.

1.6 Outline of the report

Having presented an overview here, subsequent chapters take a much more comprehensive look at the highlighted points. Chapter Two surveys the literature, which then feeds into underpinning considerations for the method adopted, explained in Chapter Three. The Results and Findings are presented in Chapter Four and summary insights, contributions, and areas for future research are discussed in Chapter Five.

2. LITERATURE REVIEW

The review centres on five major themes: efficient markets, asset pricing models, anomalies, stock market seasonality, investor overreaction and underreaction. Firstly, the concepts of efficient markets and asset pricing models are considered to establish the orthodoxy. Thereafter, anomalies are looked at in general and the contrasts with the Efficient Market Hypothesis (EMH) brought forth. As investor overreaction is a type of anomaly, the varying arguments on whether it is evidence of market inefficiency or otherwise is better contextualized having established the notion and shortcomings of efficient markets and asset pricing models. Since seasonality has been observed in studies other than overreaction and underreaction, alternative arguments are explored for why it occurs. Consequently, questions and gaps identified that establish the relevance of this study are summarized in the final section.

2.1 Efficient Markets

The notion of efficient markets extends from the Bachelier-Osborne random walk model, which posits that there should be no informational value in historical price patterns (Fama, 1965). While the random walk hypothesis (RWH) is foundational to the efficient market hypothesis (EMH) and often construed to have similar meanings, there are subtle but significant differences. The random walk model hypothesizes that security price distributions should be independent and conform to some probability distribution (Fama, 1965). That is, there should be no correlation between previous prices of a security and its future price. This is the underpinning principle behind most market efficiency tests. When some statistically significant correlation is observed, however, it only becomes evidence of inefficiency when it is persistent and economically significant.

Fama (1965) tests the empirical validity of the random walk model using the daily prices of thirty constituent stocks of the Dow Jones Industrial Average (DJIA) by, in addition to other

approaches, constructing normal probability graphs for daily changes in the natural logarithm of each security price. Its distribution of price changes showed observable departures from normality where *ex post* tests of statistical significance (serial correlation and runs tests) were deemed mostly independent, in consonance with the first assumption of the random walk model, as depicted algebraically by:

$$P(x_t = x \mid x_{t-1}, x_{t-2}, \dots) = P(x_t = x) \quad (2.1)$$

That is, the probability that a stock price change will take the value x conditional upon the knowledge that previous price changes took the values x_{t-1} , x_{t-2} , et cetera; is equal to the unconditional probability that the price change during time t will take the value x (Fama, 1965).

In addition to the serial correlation, runs and filter tests, Fama (1965:85) gives consideration to Mandelbrot's (1963) exposition that "large (price) changes may tend to be followed by large (price) changes, but of random sign, whereas small changes tend to be followed by small changes", a hypothesis that alters the independence assumption of the random walk model:

$$P(x_t = x \mid x_{t-1}, x_{t-2}, \dots) > P(x_t = x) \quad (2.2)$$

Fama (1965) found evidence of large price changes being followed by large price changes but of either sign. De Bondt and Thaler (1985) hypothesize and present evidence that show the change would be of the opposite sign. Fama's (1965) additional argument is that even when the above relation is statistically significant, it may not be economically significant. That is, statistically significant departures from normality or dependence of price change distributions may still not be strong enough to allow an investor earn profits after accounting for transaction, search and information costs.

The evolution of empirical research on efficient markets had first been concerned with the utility or otherwise, of historical information in predicting stock returns: “weak-form tests of the EMH” – autocorrelation, runs and trading rule tests – as it were. Evidence of some utility of *ex post* returns in predicting return performance (Basu, 1977; French, 1980; Banz, 1981; Keim, 1983; De Bondt and Thaler, 1985; Jegadeesh, 1990; Schwert, 1990; Jegadeesh and Titman, 1993; et cetera), dubbed anomalies, thereafter shifted the attention of researchers towards how long it took for security prices to adjust to public information as they became available, so-called “semi-strong-form tests of the EMH” – event studies. Additionally, it is intuitive to suppose that in an efficient market, certain groups of investors – corporate insiders, stock exchange specialists, professional portfolio managers, security analysts, et cetera – shouldn’t have monopoly access to information that could influence security prices and thus consistently earn above-average risk-adjusted returns. Investigations in this regard – “strong-form tests of the EMH” – have been mixed, however.

“Return prediction studies” – a broad categorization for weak-form efficiency tests by Fama (1991), continue to be challenged by the supposed inadequacies of subsisting equilibrium models. While an exhaustive pricing model based on these observations is yet to be developed, there is increasing evidence of the predictive utility of *ex post* returns in determining *ex ante* returns. The recurring question remains whether anomalies are not just evidence that an exhaustive model of factors that underpin return remains elusive. The one-factor Sharpe-Lintner-Black (SLB) asset pricing model (Sharpe, 1964; Lintner, 1965; Black, 1972) remains by far the most popular equilibrium model and yet evidence (Banz, 1981; Reinganum, 1981; Basu, 1977; et cetera) of its mis-specification of risk factors germane to asset pricing is quite substantial.

“Event studies”, a broad categorization for semi-strong efficiency tests by Fama (1991), represent much more robust efficiency tests in the sense that they are not beleaguered by the “joint-hypotheses” problem of market efficiency and asset-pricing specification (Fama, 1991). In a purely practical sense, the case can be made that uneven reactions of investors to new

information (e.g., stock splits, earnings announcement, etc.) present profit opportunities that only become insignificant when a critical mass of market participants decide to exploit the temporary “disequilibrium” at about the same time; since it pushes the price back to equilibrium as suggested by market efficiency empiricists. Thus, when factors such as market microstructure, transaction costs, et cetera are considered alongside reactions to company events, the supposed statistically significant “disequilibria” becomes economically insignificant.

“Tests for private information”, a broad categorization for strong-form efficiency tests by [Fama \(1991\)](#), investigates informational advantages that certain market actors supposedly have because of their vantage positions. [Fama \(1991\)](#) groups the relevant studies into three: (a) “Insider Trading”, (b) “Security Analysis” and (c) “Professional Portfolio Management”, and concedes that they point to statistically significant evidence of the existence of informational advantages for these market actors. In the case of market makers/specialists on the New York Stock Exchange (“Insider Trading”), [Neiderhoffer and Osborne \(1966\)](#) present evidence that show that market makers do possess information that enable them earn, on the aggregate, positive abnormal profits on a consistent basis.

In light of [Fama \(1970\)](#), the dependence test in [Fama \(1965\)](#) fall under the weak-form tests of the EMH since the focus was on whether historical prices of securities had economic utility. [Fama \(1965\)](#) had also posited that the independence of security prices’ distributions is enhanced when there are: (a) superior technicians who are able to take advantage of dependencies in security price distributions and thus render technical analysis redundant by their collective action and (b) superior fundamental analysts who are able to predict economic and political variables that have price impact on securities. It also argues that it is near impossible for any one fundamental investor to consistently earn profits in this way. Tests of this claim fall under strong-form EMH tests where institutional investors – who fit closely with the description of the fundamental analyst described above – are studied to see if they consistently earn alpha returns.

Fama (1970) examines the three models of the theory of efficient markets: (a) Expected return or “fair game” models, (b) The submartingale model and (c) The random walk model. Since the fair game model seems more exhaustive and the other types are argued to be its variants, it is presented below.

$$E(P_{j,t+1} \mid \varphi_t) = P_{jt} [1 + E(r_{j,t+1} \mid \varphi_t)] \quad (2.3)$$

This expression simply implies that the equilibrium or expected return on a security at time t+1 based on information available at time t, $E(P_{j,t+1} \mid \phi_t)$, should be the sum of the purchase price of the security P_{jt} and the expected one-period percentage return of the security at time t+1 as assessed by the market based on the available information at time t, ϕ_t .

Thus, a residual return, $U_{j,t+1}$ would be:

$$U_{j,t+1} = P_{j,t+1} - E(P_{j,t+1} \mid \varphi_t) \quad (2.4)$$

Or alternatively,

$$U_{j,t+1} = r_{j,t+1} - E(r_{j,t+1} \mid \varphi_t) \quad (2.5)$$

That is, the difference between the actual price (return) and expected price (return) as assessed by the market in a prior period based on information available to it at that time.

Further to the above, the expected return or “fair game” model of efficient market theory posits that:

$$E (U_{j,t+1} \mid \varphi_t) = 0 \quad (2.6)$$

That is, the expected residual return at time $t+1$ as assessed by the market based on information available at time t , should be zero. In other words, the actual return should be no different from that expected by the market based on information available to it in the prior period. From a statistical perspective, a violation of the above expression is evidence of inefficiency with respect to the expected return (or “fair game”) and random walk models of market efficiency.

Fama’s (1965, 1970) argument is that statistical evidence of dependence in security price distributions does not suffice in making a claim of market inefficiency. Instead, the correlation between historical prices (or returns) would have to be strong enough to leave the discerning investor with an economic profit (i.e., *ex post* transaction and ancillary costs), one which he is consistently able to earn by taking advantage of the supposed dependencies. Simply put, evidence of dependence in return distributions, though antithetical to the random walk model (one of the models of efficient market theory), may not necessarily contradict the efficient market hypothesis since it requires statistically significant correlations to also be economically significant.

Fama (1970) provides additional conditions that bolster market efficiency, one of “frictionless markets” where information is readily available and costless and expectations of its impact on security prices or returns are homogenous. While it posits that these conditions are not prerequisites to market efficiency but only enhancing factors, it remains a plausible argument that the non-existence of such market conditions in reality are antithetical to the efficient market hypothesis. The notion that investors - or at least a significant quantum - would

interpret available information in the same manner is counterintuitive and antithetical to the constitution of human beings. This is one of the foundational arguments of behavioural finance.

Surprisingly, Fama (1965, 1970) does concede to elements of the overreaction hypothesis (depicted below). In explaining the observation of consecutive large price changes in random directions as hypothesized by Mandelbrot (1963), the paper concedes that information may not necessarily be assimilated immediately and that adjustment of prices to this new information will swing between two extremes – perhaps an overreaction and underreaction – before finally stabilizing at the new equilibrium price.

$$\begin{array}{l}
 E(r_{j,t+1} \mid r_{jt}) \neq E(r_{j,t+1}) \\
 \\
 E(U_{w,t+1} \mid r_{jt}) < 0 \\
 \\
 E(U_{L,t+1} \mid r_{jt}) > 0
 \end{array}
 \left. \vphantom{\begin{array}{l} E(r_{j,t+1} \mid r_{jt}) \neq E(r_{j,t+1}) \\ E(U_{w,t+1} \mid r_{jt}) < 0 \\ E(U_{L,t+1} \mid r_{jt}) > 0 \end{array}} \right\} \begin{array}{l} \text{De Bondt and Thaler} \\ (1985, 1987) \end{array}$$

In light of above, De Bondt and Thaler’s (1985:795) hypothesis that “extreme movements in stock prices will be followed by subsequent price movements in the opposite direction” is actually an extension of the observed random directional but consecutive price changes in Fama (1965, 1970). Except for perhaps Fama’s (1965, 1970) intellectual entrenchment, De Bondt and Thaler’s (1985, 1987) overreaction hypothesis was discernible as far back as Mandelbrot (1963). Subsequent behavioural models (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998) find that investors do overreact and underreact to new information with statistically significant dependencies as have been documented by De Bondt and Thaler (1985, 1987) and the other numerous extensions of that seminal study (e.g., Chan, 1988; Chopra, Lakonishok, and Ritter, 1992). Thus, the major contribution of De Bondt and Thaler (1985, 1987) is the evidence it proffered: that in addition to the sequential

proportional price changes found in studies such as Fama (1965, 1970), the direction of the change is non-random.

The EMH continues to be tested across markets with mixed results. Karemera, Ojah, and Cole (1999) investigate 15 emerging capital markets using Chow and Denning's (1993) multiple variance ratio technique which controls for some of the observed misspecification of Lo and MacKinlay's (1988) single variance ratio random walk hypothesis test and the potential erroneous inferences therefrom. They find evidence consistent with the weak-form EMH. In light of their peculiar microstructure (e.g., exchange rate controls, price change limits, ownership, transaction costs, information costs, et cetera) and continually evolving research methodologies for efficiency and (or) random walk studies, however, the supposed weak-form efficiency in emerging markets and indeed the EMH, are still open to debate. In fact, Karamera et al. (1999) find that equity return dynamics are differential when exchange rates are taken into consideration, especially for markets with hitherto high exchange rate volatility.

2.1.1 Is the Nigerian Stock Exchange an efficient market?

Olowe (1999), using a 1981-1992 monthly return dataset for 59 randomly selected NSE-listed securities, finds the NSE weak-form efficient as did Samuels and Yacout (1981) and Ayadi (1983). Tijjani, Power, and Fifield (2009) also find this is still the case. A critique of earlier Nigerian efficiency studies (e.g., Samuel and Yacout, 1981; Ayadi, 1984) borders on small sample sizes – twenty one to thirty quoted companies – and use of weekly returns that made numerous securities in their sample that were thinly traded underestimate the variability of returns and hence bias the tests towards efficiency (Olowe, 1999). In other instances, Nigeria was part of an emerging market sample (Samuel and Yacout, 1981; Claessens, Dasgupta, and Glen, 1995; et cetera). Olowe (1999) in contrast to these earlier studies uses monthly returns of 59 randomly selected securities listed on the Nigerian Stock Exchange (NSE) for the period 1981 to 1992 and yet still finds evidence in support of the weak-form EMH. A later study (Tijjani et al., 2009) uses weekly closing prices for its autocorrelation tests, however, but for a much larger

sample of 69 NSE-listed securities for the 11-year period of 1995 – 2005 across 1-, 5-, 10- and 15-week lags. But for the observed sparing inefficiency observed for short lags, the findings of [Tijjani et al \(2009\)](#) are consistent with previous Nigerian EMH studies, in support of weak-form efficiency.

2.1.2 Is the Johannesburg Stock Exchange (JSE) an efficient market?

Using a twenty-four share sample, [Roux and Gilbertson \(1978\)](#) find statistically significant price change dependencies in the Johannesburg Stock Exchange, with a preponderance of the price change distribution being leptokurtic. [Roux and Gilbertson \(1978\)](#) suppose the concentration of price changes around the mode of the distribution and in extreme tails to be as a result of large numbers of zero price changes, especially for industrial and mining shares. Even though [Roux and Gilbertson \(1978\)](#) do not investigate the economic significance of their findings, they conjecture that the exploitation of the observed price change dependencies relative to a buy and hold strategy wouldn't be profitable.

[Page and Way \(1992\)](#) document results inconsistent with the weak-form EMH on the JSE; with the performance of the shares formed on the basis of prior return data being predictable and on average, portfolios of prior “losers” outperforming prior “winners” by about 20% over the three years after portfolio formation. They also found evidence of a January effect similar to that evidenced on the New York Stock Exchange by [De Bondt and Thaler \(1985\)](#). Other JSE studies ([Cubbin, Eidne, Firer and Gilbert, 2006](#); [Venter, 2009](#)) also find evidence of anomalies that point to inefficiency.

2.1.3 Gaps in the NSE and JSE efficiency literature

In sum, these studies are mostly differential on the basis of some statistical artefact. As earlier discussed, the concept of efficiency extends beyond statistical significance and it would indeed be rare if any proof of efficiency or otherwise is found to be consistent without some trading rule cum profitability test. The mixed results of efficiency studies for markets like Nigeria

(Olowe, 1999; Appiah-Kusi and Menyah, 2003; Tijjani et al., 2009; etc.) and South Africa (Page and Way, 1992; Roux and Gilbertson, 1978; Cubbin et al., 2006; etc.) – especially in light of their contrasting institutional infrastructure – is suggestive of empirical and perhaps theoretical gaps. Relevant research questions in this regard thus include whether the observed overreaction and January effects on the Johannesburg Stock Exchange (e.g., Page and Way, 1992; Bradfield, 1990; Muller, 1999; Robins et al., 1999; Cubbin et al., 2006; Venter, 2009; Hsieh and Hodnett, 2011; etc.) are persistent. For the Nigerian Stock Exchange, the points of enquiry revolve around whether its supposed weak-form efficiency (e.g., Olowe, 1999; Tijjani et al., 2009; Okpara, 2010; etc.) is robust to the overreaction and January effects. Furthermore there is a need to explain why January returns were differential in prior studies (e.g., De Bondt and Thaler, 1985, 1987; Jegadeesh, 1990; Page and Way, 1992; Robins et al., 1999; Cubbin et al., 2006; et cetera).

2.2 Asset Pricing Models

The search for a robust asset pricing model is longstanding and continuing. In fact, model misspecification remains a recurring rebuttal to purported anomalies, especially those observed relative to the Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Black (1972). Other prominent models include Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), the Arbitrage Pricing Model (Ross, 1976), and the Three-Factor Model by Fama and French (1993, 1996).

2.2.1 The Capital Asset Pricing Model

The underlying assumptions of the Sharpe-Lintner-Black Capital Asset Pricing Model (SLB CAPM) extend from Markowitz' (1952) mean-variance portfolio model which essentially opines that investors want a portfolio that would produce the best return for the least risk, a mean-variance efficient portfolio. Additional assumptions by Sharpe (1964) and Lintner (1965) are that investors have homogenous expectations of returns and can borrow and lend freely at the risk-free rate. Black (1972) reckons *a priori* that the unrestricted risk-free borrowing and lending assumption of the CAPM is differential to the validity of the CAPM and wonders whether the

model would still hold if it were dropped. This is the *raison d'être* of Black (1972). Thus, Black (1972) extends these assumptions to a scenario where there is no risk-free asset. That is, borrowing and lending the risk-free rate is not allowed. In another scenario, Black (1972) assumes there is a riskless asset in which investors can take long but not short positions. These new assumptions, Black (1972) finds, do not distort the linear relationship between beta and expected return expounded by Sharpe (1964) and Lintner (1965).

Following from the above assumptions, the SLB CAPM is expressed as follows:

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f] \quad (2.7)$$

Where $\beta_i = \text{Cov}(R_i, R_m) / \sigma^2(R_m)$, $E(R_i)$ is the expected return on asset i , R_f is the risk-free rate, $E(R_m)$ is the expected return on the market portfolio and β_i is the slope of the regression line relating R_i and R_m .

The thesis of the SLB CAPM is that beta has robust explanatory power for expected returns. There are studies (Basu, 1977; Banz, 1981; Fama and French, 1992, 1993 and 1996; et cetera), however, that suggest otherwise. Factors now considered to be unexplained by the CAPM include size (Banz, 1981), ratio of share price to book value per share (P/B) (Fama and French, 1992), ratio of share price to earnings per share (P/E) (Basu, 1977), return persistence (Jegadeesh and Titman, 1993 and 2001), return reversal (De Bondt and Thaler, 1985 and 1987), et cetera.

Fama and French (2004) argue that the major flaw in the SLB CAPM lies in its unrealistic assumptions: unrestricted risk-free lending and borrowing (Sharpe, 1964; Lintner, 1965) or unrestricted short-selling in the absence of a riskless asset (Black, 1972) is simply impracticable. It is also counterintuitive for investors to think alike and have similar expectations, otherwise the whole essence of markets would be lost. However, modelling complex situations often requires starting from an idealized scenario relative to which some empiricism is possible. In an ideal world, all investors would like to borrow freely at the risk-free rate. That is simply

impossible, however, because investors are not necessarily under the same constraints or endowed similarly.

Black (1972) theorizes that in the absence of a risk-free security/asset to borrow or lend, investors would have to choose from assets in the risky portfolio and that the CAPM would still hold if there is “unrestricted short sales of risky assets.” A logical extension of the Sharpe-Lintner CAPM assumptions of homogeneity of investor expectations and risk aversion suggest that the investor would either hold the risk-free portfolio or a combination of the risk-free and risky assets. The difference in return thereof might only then be in how much of the risky asset they hold and how much of the risk-free asset to lend or borrow to enhance their return by going long or short the risky asset. This assumed homogeneity of expectations suggests that all investors would hold the same portfolio of risky assets but in different proportions (or weights).

Essentially, tests of the CAPM seek to investigate whether the market portfolio is indeed efficient. The implications thereof are that asset expected returns should be directly proportional to their market betas, the additional premium over the return of the risk-free asset for the additional risk taken in investing in the risky asset should be positive and the intercept of the linear relationship between expected returns and beta should be the risk-free rate (Fama and French, 2004).

Early tests of the SLB CAPM fall into two categories: Cross-sectional and time-series regression tests. Cross-sectional tests (Friend and Blume, 1970; Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973; et cetera) involve regressing “average security returns on estimates of their market betas” – so called cross-section regression tests of the CAPM – whereby a positive slope and intercept equal to the risk-free rate is seen as evidence that the above relations hold. In a time-series test, however, the intercept term is expected to be zero for each asset.

Friend and Blume (1970) analyze the extent to which CAPM betas measure the risk they are supposed to abstract. They present evidence that show that beta is biased against risky portfolios – that is, *ex post* returns (risk) for risky portfolios were higher (lower) than the *ex*

ante predictions of the CAPM – and relate it to one of the assumptions of the version of the CAPM – equal lending and borrowing rates – by Sharpe (1964) and Lintner (1965).

Additionally, Black, Jensen and Scholes (1972), Fama and MacBeth (1973) and Fama and French (1992) find that the intercept term in their cross-sectional regression tests is greater than the one-month treasury bill rate – the typical proxy for the risk-free asset – and the coefficient of beta is less than the excess market return over the risk-free asset. Similarly, time-series tests of the CAPM find non-zero intercept terms in their regressions (e.g., Friend and Blume, 1970; Black, Jensen and Scholes, 1972; Stambaugh, 1982).

Fama and French (2004) argue that cross-section and time series regressions do not suffice to test the assertions of the CAPM and that what they really test is how efficient a specific proxy for the market portfolio is (Jensen, 1968; Friend and Blume, 1970; et cetera). In fact, Roll (1977) argues that the CAPM has not been tested hitherto and that a market portfolio in the form suggested by the SLB CAPM would continue to be elusive.

Thus, there is some merit in the argument that the purported misspecification of the SLB CAPM is simply due to a weak proxy for the market portfolio of invested wealth. Thus far, this proxy has typically been the return to a stock market index. However, Stambaugh (1982) provides evidence that show a much more inclusive or broader market proxy would not be differential to the robustness of the CAPM; as stock returns account for most of the volatility of the broader market. In any case, Fama and French (1997), Pastor and Stambaugh (1999), et cetera, argue that the estimation of key variables (β , $R_m - R_f$) of the CAPM are flawed by their accompanying large standard errors and that the CAPM's chances are jeopardized irrespective of the market proxy problem.

While they provide some accommodation for Black's (1972) model, being as it is that it recognizes that the relationship between average expected returns and market beta is flatter than predicted by the earlier version of the CAPM by Sharpe (1964) and Lintner (1965), Fama and French (2004) write off the latter as an empirical failure. Undoubtedly, the discovery of other factors (e.g. size, value, momentum, et cetera) with explanatory power for asset returns

does raise questions about the specification of the SLB CAPM. If in spite of its empirical flaws, however, the SLB CAPM has become the preeminent rational pricing benchmark (Fama and French, 2004; Da, Guo, and Jagannathan, 2012), the behaviouralist argument that deviations from the predictions of the SLB CAPM is irrational – an overreaction and/or underreaction as the case may be – has some merit. Fama and French (2004) adopt the rationalist view, however, that returns in excess of that predicted by the SLB CAPM are premia for risks that it doesn't capture. Incidentally, their three-factor model is not exhaustive either. The momentum effect as expounded by Jegadeesh and Titman (1993) is certainly one “anomaly” it has not been able to explain.

Bottom-line is that there are elements of return that the CAPM has not been able to explain. It may be due to the market proxy problem or the estimation errors in the computation of beta and the market premium or indeed misspecification of the model itself. In a survey of Chief Financial Officers by Graham and Harvey (2001), 73.5% admitted to using the CAPM in their capital budgeting process. Similarly, 75% of finance professors surveyed by Welch (2008) teach and recommend the CAPM in their courses. Thus, while criticisms of the CAPM (e.g., Fama and French, 1992, 1993, 1996 and 2004) persist, it continues to be the pre-eminent asset pricing model in finance (Da, Guo, and Jagannathan, 2012).

2.2.2 The 3-factor model

Following Merton's (1973) Inter-temporal Capital Asset Pricing Model (ICAPM) and Ross' (1976) Arbitrage Pricing Model, Fama and French (1993 and 1996) propose a multifactor ICAPM that adds two more variables to the classical model, a so-called Three-Factor Model.

$$E(R_i) - R_f = b_i [E(R_m) - R_f] + S_i E(SMB) + h_i E(HML) \quad (2.8)$$

$$R_i - R_f = \alpha_i + b_i (R_m - R_f) + S_i SMB + h_i HML + \varepsilon_i \quad (2.9)$$

Essentially, it posits that apart from market risk, the cross-section of average returns is explained by two additional factors: Size and the Book-To-Market Equity ratio. In the above equation, SMB is the difference in the returns of diversified portfolios of small-firm and big-firm stocks by market value and HML is the difference in the returns of diversified portfolios of high and low book-to-market equity stocks.

In [Fama and French \(1996\)](#), time-series regressions of stock returns in excess of the risk-free rate on $R_m - R_f$, SMB and HML produce intercepts close to zero, a feat most tests of the CAPM ([Friend and Blume, 1970](#); [Black, Jensen, and Scholes, 1972](#); [Stambaugh, 1982](#); et cetera) didn't achieve. As a result, [Fama and French \(1996\)](#) argue that while SMB and HML are proxies for "risk factors or state variables of special hedging concern to investors" as opposed to being the state variables themselves, their empirical success, albeit [Jegadeesh and Titman \(1993\)](#) remain doubters, suggest it is the closest there has been to an equilibrium pricing model.

There is some distinction, however, in how the SLB CAPM and the 3FM evolved. The former evolved from pre-existing theory ([Markowitz, 1952](#)) and was motivated by a need to model portfolio return under uncertainty ([Friend and Blume, 1970](#)). However, the 3FM was an empirical discovery for which theoretical meaning was sought *ex post* and this remains a major shortcoming of the model ([Fama and French, 2004](#)). In any case, it is not exhaustive either. In fact, [Fama and French \(1996 and 2004\)](#) acknowledge that their model doesn't explain [Jegadeesh and Titman's \(1993\)](#) momentum effect. While in their own tests ([Fama and French, 1993, 1996 and 2004](#)), they present evidence showing that the overreaction effect is simply the result of the misspecification of the CAPM, there have been studies (e.g., [Assoe and Sy, 2003](#); [Chiao and Hueng, 2005](#)) robust to the 3FM model.

[Carhart \(1997\)](#) proposes a "momentum factor" as a fourth factor to [Fama and French's \(1993 and 1996\)](#) three-factor model; a four-factor model. [Fama and French \(2004\)](#) argue, however, that constituents of the cost of equity should be contemporaneous with the long-term horizon of equity investors. As the momentum effect is a fleeting phenomenon, they suggest that a

“momentum factor” may not be appropriate; at least with respect to computing the cost of equity.

2.2.3 Summary insights on asset pricing models

A major issue of interest here is the discountenance of [De Bondt and Thaler's \(1985\)](#) overreaction effect by [Fama and French \(1996\)](#), wherein they argue that the misspecification of the CAPM is actually responsible for the purported anomaly. In regard of the continuation of short-term returns, that is, the momentum effect or investor underreaction ([Jegadeesh and Titman, 1993](#)), [Fama and French \(1996\)](#) argue that the inability of their model to explain it is as much a challenge for behavioural finance as it is for conventional finance theory. This is because, hitherto, there was – there still is perhaps – a seeming contradiction between the supposition that short-term return continuation was as a result of investors' underreaction and return reversal was as a result of investor overreaction (see [Lakonishok, Shleifer, and Vishny, 1994](#)). Considering that short-term return reversals have been evidenced as well ([Jegadeesh, 1990](#); [Lehman, 1990](#); et cetera), short-term return continuation ([Jegadeesh and Titman, 1993](#)) and the seeming contradiction highlighted above raise questions about the relationship between return persistence and return continuation. [Barberis et al. \(1998\)](#), [Daniel et al. \(1998\)](#), [Hong and Stein \(1999\)](#) and [Jegadeesh and Titman \(2001\)](#) explore this relationship. Additionally, [Jegadeesh and Titman \(2001\)](#) verify whether the evidence of investor under-reaction in [Jegadeesh and Titman \(1993\)](#) could be refuted by the data-snooping argument of [Lo and MacKinlay \(1990\)](#); a discussion to be found in subsequent sections on investor overreaction and underreaction.

In regard of the CAPM, it could be argued that a true market portfolio would be reflective of the factors that explain returns: known and unknown; and that perhaps, the real task lies in finding the true market portfolio of invested wealth or as close a proxy we can find. This theoretical and (or) empirical gap in finding a robust and properly specified asset pricing model provides opportunities for discovering the other unknown factors that affect the expected return of

assets. Further work in this regard would most likely build on existing models as the discoveries of these new factors are made.

In simple terms, an anomaly only exists relative to a consensus of what “normal” is. What is “normal” would continue to evolve as additional factors with explanatory powers for asset returns are discovered. From an investor/practitioner lens, however, these supposed anomalies would present alpha opportunities until the consensus on what “normal” is, shifts to include what was considered an anomaly.

A plausible alternative argument could also be that as anomalies are discovered and found to be enduring, they would evolve into additional factor(s) in existing asset pricing models and the beta interpreted as a factor sensitivity for a portion of market risk and that other factors are explanatory variables for other portions of market risk that we do not as yet grasp fully.

In any case, the behaviouralist view that the SLB CAPM is the rational pricing benchmark and that deviations from its predictions are anomalies due to irrational reactions to information (Fama and French, 2004) has merit when the quantum of market players that use the model is considered (Graham and Harvey, 2001; Da, Guo, and Jagannathan, 2012).

2.3 Anomalies

Market efficiency studies are constantly evolving as some earlier discovered anomalies either disappear or evidence is found suggesting them to be spurious. Schwert (2002) investigates the persistence of anomalies *ex post* their popular discoveries and finds that most of them seem muted or all together disappeared except for the January effect. This is pertinent because of the distinctions made between mispricings and anomalies; the latter being more persistent thereby qualifies as plausible evidence against market efficiency. It would seem now, however, that the January effect and its consistency thus far pose the greatest challenge to the validity of the EMH. Some of the prominent anomalies include the size effect (Banz, 1981; Reinganum, 1981), earnings-yield effect (Basu, 1977 and 1983), January effect (Rozeff and Kinney, 1976;

Keim, 1983; Reinganum, 1983), Weekend or Monday effect (French, 1980), Winner-Loser or Overreaction effect (De Bondt and Thaler, 1985 and 1987; Jegadeesh, 1990; Chan, 1988), Underreaction effect (Jegadeesh and Titman, 1993 and 2001), et cetera. Some are discussed below and the ones pertinent to this study, the overreaction and January effects, are discussed in separate sections.

2.3.1 Earnings yield effect

Basu (1977) proposes a price-ratio hypothesis that posits that firms with high earnings yield (E/P), or low Price-Earnings (P/E) ratios, earn higher returns than firms with low earnings yield (high P/E ratios) – an E/P effect. Ranking New York Stock Exchange (NYSE)-listed firms by P/E ratios for the period 1957 to 1971, Basu (1977) finds that low P/E (high E/P) portfolios earn higher risk-adjusted returns than high P/E (low E/P) firms. Additionally, its findings show that the low P/E portfolios earn 2% per month more than the return implied by their level of risk and the high P/E portfolios earn 3% per month less than that implied by their level of risk. When juxtaposed with the intuition of higher systematic risk (and thus higher returns relative to low P/E portfolios) for the high P/E portfolios, it is counterintuitive for the lower P/E ratios to earn statistically significant higher returns than the high P/E portfolios. This of course bolsters the argument for the joint hypotheses problem associated with efficiency studies. In any case, Basu's (1977) findings do suggest that the equilibrium model used is mis-specified and as such one cannot conclusively posit that the E/P effect is evidence of inefficiency.

2.3.2 Size effect

The "Size Effect" or "Value Effect" was first documented by Banz (1981). As opposed to identifying it as another anomaly, he preferred the argument that the equilibrium model used in the study was mis-specified. It found excess return on an arbitrage portfolio that was long small firms and short very large firms, to be on average 1.52% per month (19.8% on an annualized basis).

Basu (1983) seems to suggest that the supposed size effect (Banz, 1981; Reinganum, 1981) is an instance of the earnings yield (E/P) effect. Basu's (1983) inconclusiveness, however, means the assertions of Reinganum (1981) in particular, cannot be discountenanced. Reinganum (1981) had used a 2-way classification scheme for a sample that had exhibited the size and E/P effects to form portfolios that controlled for the E/P effect in its investigation of the linkages between the two anomalies. In each E/P quintile portfolio, securities in each of the market value quintiles were included. The study's findings showed that in each E/P quintile, the smallest firms outperformed the largest ones with statistical significance. This highlights evidence of a size effect irrespective of a security's price-earnings ratio (P/E). The foregoing shares a commonality, however. That is, the Sharp-Lintner-Black (SLB) CAPM model is mis-specified and the size or E/P effect (or both) are proxies for one of the risk variables germane to asset pricing.

Siegel (2007) makes the case for a time-period bias in prior tests for the size effect. Analysing data outside of the nine year period of 1975 to 1983 – a period for which the small cap effect in U.S stock returns has been found to be concentrated wherein as a group, they outperformed large cap stocks by 19.6 percent annually – the study found that a given investment in large-cap equities for the period 1926 to 2001 achieved an equivalent return (9.59%) as an investment in small caps (9.61%) that excluded the aforementioned period.

2.3.3 Monday or weekend effect

In investigating the seemingly consistent negative returns on Mondays for the U.S equity market (i.e., a Monday or Weekend effect), French (1980) tests two prominent models of the return generating process, namely the calendar time and trading time hypotheses. That is, he examines whether returns are generated continuously (calendar time) or only during trading days or periods (trading time). If the trading time hypothesis were true, then the observed negative returns associated with Mondays would not be statistically different from those earned during the remaining trading week.

Using daily returns to the S&P composite portfolio for the period 1953 – 1977, [French \(1980\)](#) investigates the trading time question using a regression model that deploys dummy variables to indicate the day of the week, with a null hypothesis of there being no statistically significant difference in the regression coefficients. The tests were statistically significant enough to reject the null hypothesis of non-differential returns across trading days, thus allowing for the rejection of the trading time hypothesis and supporting evidence of a Weekend effect or Monday effect.

Under the calendar time model, Monday's expected return should be three times that of the other days of the week, thereby accounting for the two non-trading days – Saturday and Sunday – of the week. That is, if expected returns are not differential across each day (or their difference is not statistically significant), Monday's return should reflect the returns of the prior two non-trading days that hitherto had no medium for reflecting investors' assessment of share values. Except for the sub-period of 1973 – 1977, [French \(1980\)](#) finds the tests for the calendar and trading time hypotheses to be statistically significant.

As a potential explanation, [French \(1980\)](#) highlights the tendency of firms to release “bad news” over the weekend to allow investors time to digest the new information and thus minimize its price impact come the trading day. As a potential explanation, it is faulty and [French \(1980\)](#) acknowledges as much. This is because it is unrealistic to suppose that there would always be bad news for every security in every weekend.

2.3.4 The unexplained anomaly: January effect

Out of all the anomalies that [Schwert \(2002\)](#) investigates, the January effect stands out as the only one that has not been overwhelmed by arbitrage. In a regression of the return difference between small- and large-firm portfolios on a dummy variable for the month of January, [Schwert \(2002\)](#) finds the January coefficient to be 0.8% per day for the 1962-1979 period and about half that amount for the later period of 1980-2001. While the results suggest the January

seasonal is not as strong as it is used to be, it nonetheless shows that the anomaly remains persistent.

2.4 Investor Overreaction

Evidence of price reversals was documented before any of the efficiency arguments. In fact, [Niederhoffer and Osborne \(1966\)](#) observed that price changes in one direction were followed by price changes in the other direction when it studied the six stocks in the Dow Jones Industrial Average (DJIA) for the twenty-two (22) trading days of October 1964. With the benefit of hindsight, their observation improved upon [Mandelbrot's \(1963:418\)](#) exposition that for security prices, "large price changes tend to be followed by large price changes – of either sign – and small changes tend to be followed by small changes." Perhaps, [Niederhoffer and Osborne's \(1966\)](#) seminal evidence of price reversals didn't enjoy the prominence that a similar study enjoyed nineteen years later because of the very small sample (six stocks) used in their study and the less than sophisticated methodologies available at the time.

[De Bondt and Thaler \(1985\)](#) posit that stock returns are predictable based on their past performance in contrast to the weak-form efficient market hypothesis and as such stock prices will exhibit mean reversion due to investors' overreaction. They premised their study on research in experimental psychology, which suggested that in violation of Bayes' rule, most people tend to overreact to unexpected and dramatic events and thus wondered if such behaviour affected stock prices. They document results consistent with the predictions of this overreaction hypothesis where portfolios of past "losers" were found to outperform past "winners", a contrarian strategy: buying stocks that performed poorly and selling those that performed well, in this case, over the previous 3 years achieved abnormal returns over a 3-year holding period.

For shorter investment horizons, [Jegadeesh \(1990\)](#) documents evidence of economically significant return reversals when investigating the profitability of the contrarian strategy over a

one-month time horizon for the period, 1934 – 1987, in the U.S equity market. The study observed positive difference in alphas of the extreme decile portfolios ranging from 2.2% to 4.37% per month; with the upper limit of 4.37% attributable to January alone. The seasonality in the study's serial correlation patterns was very obvious.

A plausible argument against [De Bondt and Thaler \(1985\)](#) would be that though it found evidence of dependence in price distributions that were statistically significant, in the absence of accounting for transaction costs, its evidence could not be said to be economically significant and the EMH would still subsist as an explanation of security prices behaviour.

[Fama and French \(1996\)](#) provide an alternative explanation for the observed positive excess return performance of loser portfolios in [De Bondt and Thaler's \(1985 and 1987\)](#) studies by showing the connection of the anomaly with size when their three-factor model [Fama \(1992 and 1993\)](#) is used as the benchmark. They were however not able to refute [Jegadeesh and Titman's \(1993\)](#) claims about the momentum effect.

[Chan \(1988\)](#) challenges the interpretation of [De Bondt and Thaler \(1985 and 1987\)](#) as evidence of market inefficiency and proffer evidence of supposed flaws in that seminal study. In addition to replicating [De Bondt and Thaler's \(1985 and 1987\)](#) methodology, [Chan](#) considers certain variations for a control sample that allows for a higher number of securities in the extreme portfolios over and above the maximum of thirty-five (35) in [De Bondt and Thaler \(1985 and 1987\)](#). Under the assumption that market value proxies for risk, [Chan \(1988\)](#) shows how the market value of losers decrease by almost 50% on average over the various portfolio formation periods between 1932 – 1983, and thus argues that the formation period ("rank period") betas in [De Bondt and Thaler \(1985\)](#) underestimate the holding period ("test period") betas of losers and thus ought not to be used in calculating risk-adjusted returns. [Chan's \(1988\)](#) modifications to the research design responsive to the aforementioned reservations result in very small abnormal returns to the contrarian strategy which in turn challenges the findings of [De Bondt and Thaler \(1985 and 1987\)](#).

Chopra, Lakonishok and Ritter (1992) also use test period betas for risk adjustment in their overreaction study and yet the contrarian portfolios earn statistically and economically significant abnormal returns in contradiction to Chan's (1988) assertions. They investigate the beta, size and seasonality arguments with respect to the market overreaction anomaly, using NYSE returns for the period 1926 – 1986. Their study is pertinent because they proffer evidence that refutes the argument that the positive excess returns of loser and arbitrage loser-winner portfolios are due to a size effect or can be explained by the difference in beta. Essentially, Chopra et al. (1992) construct separate portfolios on the bases of ranking period returns (using betas estimated via a 60-observation regression of monthly returns during the ranking period) and betas, to see whether the outcomes would be as predicted by the Sharpe-Lintner-Black model. It follows therefore, that the higher beta portfolio (supposedly analogous to the loser portfolio) would earn higher returns than the lower beta portfolio (supposedly analogous to the winner portfolio) because of its higher risk; evidence which would bolster the argument by Chan (1988) that when the beta in De Bondt and Thaler's (1985 and 1987) portfolios are properly estimated, the loser portfolios are actually riskier than the winner portfolios. Alpha of the arbitrage portfolio long losers and short winners formed on the basis of beta is -5.1% per year, a sharp contrast to the 2.5% earned by that formed on the basis of prior returns (Chopra et al., 1992, Table 1, p. 241).

In response to Zarowin's (1990) assertion that on average, losers are smaller than winners and allusion that the winner-loser effect might just be a manifestation of the size effect, Chopra et al. (1992) construct size control portfolios, that is, prior-return loser and winner portfolios are constituted using securities with an even spread across size (or market value) quintiles such that they are not dominated by small firms. This enables one to see whether in spite of this type of constitution, there would still be an overreaction effect. Their evidence suggests the effect is accentuated and economically significant over and above any size effect. Additionally, Chopra et al. (1992) use a multiple regression that simultaneously controls for size and beta and still find that "extreme losers outperform extreme winners by 4.826% per year on average for

the five post-ranking years” [Chopra et al. \(1992:253\)](#). Their results also show the independence of the size and January effects: for when the 5-year ranking period arbitrage portfolios are controlled for firm size and correlation of size with prior returns, most of the excess returns are earned in the month of January. An interesting dimension, however, is that the portfolios formed on the basis of prior 1-year returns show momentum in the next year, perhaps underscoring the varying time horizons for price reversals since shorter-term price reversals have also been documented ([Jegadeesh, 1990](#); [Lehman, 1990](#); [Venter, 2009](#)).

Using a U.K. dataset spanning December 1964 to June 2005, [Galariotis, Holmes, and Ma \(2007\)](#) test the robustness of some of the varied explanations – risk ([Chan, 1988](#); [Fama and French, 1996](#)), firm size ([Zarowin, 1990](#)), thin-trading ([Jegadeesh and Titman, 1995](#)), seasonality ([Zarowin, 1990](#)) and survivorship bias ([Lo and MacKinlay, 1990](#)) – offered for the overreaction effect hitherto (some of these have been discussed earlier). They also investigate the strength of the explanations given for the converse, or as some ([Barberis, Shleifer, and Vishny, 1998](#); [Daniel, Hirshleifer, and Subrahmanyam, 1998](#); [Hong and Stein, 1999](#); [Lee and Swaminathan, 2000](#)) argue, contiguous underreaction effect.

[Galariotis et al. \(2007\)](#) find the January seasonal to be non-differential to both the contrarian and momentum strategies; albeit for raw returns. In fact, when January returns are excluded, they find more statistically significant and profitable strategies – from 15 to 18 for the momentum strategies and 9 to 14 for contrarian strategies – out of the 64 momentum and contrarian strategies they consider. Also, their momentum and contrarian profits are robust to adjustment for market risk (proxied by the SLB CAPM beta). When [Fama and French’s \(1993\)](#) three-factor model is used as the benchmark, however, the contrarian profits largely disappear; evidence consistent with the risk argument of [Fama and French \(1996\)](#). For the momentum profits, however, [Galariotis et al. \(2007\)](#) find that they are not overwhelmed by the three-factor model. In fact, the number of momentum portfolios that record statistically significant risk-adjusted profits increases. Additionally, [Galariotis et al. \(2007\)](#) confirm that sample-period, survivorship, non-synchronous trading and bid-ask spread biases are differential to the

profitability of contrarian and momentum portfolios for stocks listed on the London Stock Exchange.

Another U.K. study offers interesting contrasts. [Spyrou, Kassimatis, and Galariotis \(2007\)](#) analyses data from four major U.K equity indices: the FT30 (large cap), FTSE100 (large cap), FTSE250 (medium cap) and FTSE Small Cap. [Spyrou et al. \(2007\)](#) find that large-cap investors react efficiently to new information about their holdings and thus didn't find any statistically significant risk-adjusted (β , SMB and HML) momentum and contrarian profits for this firm-size stratum. They conjecture this to be due to the wider analyst coverage and investor interest large caps enjoy relative to medium- and small caps. An intuition that is plausible in light of the underreaction of medium- and small-cap investors to market shocks in that study. Additionally, their results are robust to seasonal and bid-ask spread biases.

Another rational hypothesis for the overreaction effect is related to taxes. [George and Hwang \(2007\)](#) conjecture that the return reversals in U.S. stock returns can be traced to locked-in capital gains, especially since in an out-of-sample test using returns data for Hong Kong where capital gains are not taxed, they do not find reversals. [George and Hwang \(2007\)](#) rely on the seasonality observed in previous overreaction studies (e.g., [De Bondt and Thaler, 1987](#); [Grinblatt and Moskowitz, 2004](#)) to conjecture that long-term reversals can be explained by the tax-loss selling hypothesis. In any case, [George and Hwang \(2007\)](#) confirm further that loser reversals occur mostly in the calendar month of January.

[Kryzanowski and Zhang \(1992\)](#) test the overreaction hypothesis using monthly data for stocks listed on the Toronto Stock Exchange over the 1950-1988 period, and unlike [De Bondt and Thaler \(1985 and 1987\)](#), they didn't find statistically significant reversal behaviour for periods beyond one and two year(s) for winners and losers. On the trail of [Kryzanowski and Zhang](#), [Assoe and Sy \(2003\)](#) examine the profitability of the short-run contrarian strategy for the Canadian equity market, whereby "losers" and "winners" of the previous month are bought and sold respectively. They use an extension of [Fama and French's \(1993\)](#) three-factor model,

thereby taking into account, in addition to market risk, the size and book-to-market risks. They document results similar to that of [Jegadeesh \(1990\)](#) in the U.S market whereby significant abnormal returns are achieved by purchasing losers and selling winners of the previous month. They recorded a 26.25% annual average excess unrestricted return for this short-term contrarian investment strategy, a disproportionate part of which was driven by small firms, especially in January; evidence not dissimilar to [De Bondt and Thaler \(1985 and 1987\)](#) albeit for a much shorter time horizon. Upon adjusting the data for calendar month and firm size, they found the profitability of the short-term contrarian strategy to be disproportionately tilted towards small firms, especially in the January calendar month.

[Dhouib and Abaoub \(2007\)](#) document the existence of mean reversion and momentum behavior in the Tunisian stock market over the 9-year period between January 1997 and December 2005. In arriving at this conclusion, they applied the contrarian strategy of buying the previous (12-, 18-, 24- and 36-month) loser portfolio and selling the past, corresponding, winner portfolio. In a similar study conducted for the Istanbul stock exchange, [Bildik and Gulay \(2007\)](#) find, for data over the 10-year period 1991 to 2000 that contrarian strategies earn abnormal profits, evidence consistent with the predictions of the overreaction hypothesis.

2.4.1 Empirical gaps in the overreaction literature for the JSE and NSE

For the South African equity market, [Page and Way \(1992\)](#) used returns data over the period of July 1974 to June 1989 for 204 relatively well-traded securities listed on the Johannesburg Stock Exchange (JSE) to investigate the overreaction hypothesis. They document results consistent with the hypothesis and thus inconsistent with the weak-form EMH; with the performance of the shares formed on the basis of prior return data being predictable and on average, portfolios of prior “losers” outperforming prior “winners” by about 20% over the three years after portfolio formation. They also found evidence of a January effect similar to that evidenced on the New York Stock Exchange by [De Bondt and Thaler \(1985\)](#), an observation which calls into question the hypothesis that this is due to tax loss selling by investors; South African companies

are free to choose their tax year ends. Subsequent JSE overreaction studies ([Cubbin, Eidne, Firer and Gilbert, 2006](#); [Venter, 2009](#)) confirm [Page and Way's \(1992\)](#) findings of overreaction in the South African equity market. It is not known, however, whether the supposed weak-form efficient Nigerian equity market ([Tijjani et al., 2009](#)) is robust to the overreaction effect; as a survey of the literature suggests there isn't a published overreaction study of Nigeria.

To reduce stock price volatility, the Nigerian Stock Exchange (NSE) puts a cap and floor on daily price movements for its listed stocks. Intuitively, this should lead to a delay in convergence of prices to intrinsic values or perhaps overreaction at the next opportunity as investors look to key in their trades before the daily price limits are again reached. The prominent explanations for the consequences of daily price limits ([Lehmann, 1989](#); [Kim and Rhee, 1997](#); [Huang, Fu, and Ke, 2001](#); [Cho, Russell, Tiao, and Tsay, 2003](#)) suggest outcomes converse to market efficiency. Yet most studies of the NSE suggest it is weak form efficient (e.g., [Olowe, 1999](#); [Tijjani et al., 2009](#)).

[Lin and Swanson \(2010\)](#) wonder if price limits hinder the profitability of contrarian strategies. Since a survey of the literature suggests there is yet to be an overreaction study for the Nigerian equity market, [Lin and Swanson's \(2010\)](#) evidence of contrarian behaviour in the price-limit regulated Taiwanese equity market suggest inferences that make the supposed weak-form efficiency of the similarly price-limit regulated Nigerian equity market suspect.

2.5 Investor Underreaction

In contrast to long-term return reversals (De Bondt and Thaler, 1985) and short-term return reversals (Jegadeesh, 1990; Lehman, 1990), Jegadeesh and Titman (1993) document short-term return continuation using a relative strength trading strategy; that is, buying stocks that have performed well in the past (“winners”) and selling those that have performed poorly in the past (“losers”). Momentum portfolios constituted by selecting stocks based on their six-month historical returns and holding them for another six months produce average compounded excess return of 12.01%. Jegadeesh and Titman (1993) attribute this phenomenon to “delayed price reactions to firm-specific information,” – investor underreaction.

Interestingly, however, much of the excess momentum portfolio returns in Jegadeesh and Titman (1993) begins to dissipate twelve months after the portfolio formation month; return reversals consistent with De Bondt and Thaler’s (1985) investor overreaction. Barberis et al. (1998); Daniel et al. (1998); and Hong and Stein (1999) present models of investor sentiment that attempt to reconcile the initially seeming contradiction between the empirical findings of overreaction (De Bondt and Thaler, 1985; Jegadeesh, 1990) and underreaction (Jegadeesh and Titman, 1993). These behavioural models suggest underreaction and overreaction to be elements of the return generation cycle and predict that momentum profits that accrue due to investor underreaction should turn negative 13 to 60 months after the portfolio formation month when hitherto slow-reacting investors overreact to long-running and trending information they had hitherto been oblivious (or ambivalent) about.

Lee and Swaminathan (2000) present evidence showing underreaction and overreaction are linked by trading volume proxied by the turnover ratio (defined as the daily ratio of traded shares to the number of shares outstanding for each stock). They create momentum portfolios based on historical trading volume that exhibit intermediate-horizon return continuation along the lines of Jegadeesh and Titman (1993) and long-horizon return reversal as predicted by De Bondt and Thaler (1985). What is particularly interesting in Lee and Swaminathan (2000) is their assertion about the utility of historical trading volume in predicting the timing of return

reversals. This is not an empirical artefact, however. [Campbell, Grossman and Wang \(1993\)](#) and [Blume, Easley, and O'Hara \(1994\)](#) provide theoretical evidence that show strong linkages between stock returns and trading volume.

After separately ranking stocks based on their historical returns and trading volume, [Lee and Swaminathan \(2000\)](#) form thirty “price momentum-volume portfolios” that consist of stocks common to individual strata in both rankings. These portfolios are then held for varying periods ranging from three months to five years. The arbitrage momentum portfolio – one that is long extreme decile winners and short extreme decile losers – is profitable in the first year with returns ranging from 10.62 percent to 12.70 percent per year. A strong reversal pattern occurs, however, in the fourth year and endures to the fifth; with the portfolio recording negative returns irrespective of the formation period. Additionally, the extreme winner and loser portfolios share a commonality: they are characterized by high trading volume stocks.

Another remarkable finding in [Lee and Swaminathan's \(2000\)](#) study is the better holding period return performance recorded by stocks with low volume turnover ratios during the portfolio formation period irrespective of whether they are winners or losers. For portfolios formed based on prior nine-month historical metrics and held for another six months, low volume losers (winners) outperformed high volume losers (winners) by 1.02 (0.26) percent per month ([Lee and Swaminathan, 2000](#)). However, this is inconsistent with the stronger momentum effect associated with high trading volume stocks.

In sum, when the views of [Lee, Myers, and Swaminathan \(1999\)](#) that the market continually iterates towards fundamental value convergence is considered, the intuition by [Lee and Swaminathan \(2000\)](#) that underreaction and overreaction are simply contiguous elements of a continuous cycle that characterize how investors act on new information, seem a plausible reality. Incidentally, their findings support this theory.

[Jegadeesh and Titman \(2001\)](#) present evidence consistent with the predictions of the aforementioned behavioural models. They form relative strength portfolios using data over the 1990 to 1998 period, and confirm the persistence of the short-term return continuation

observed in [Jegadeesh and Titman \(1993\)](#). Additionally, they confirm the return reversals of winner and loser stocks 13 to 60 months after the portfolio formation month, with hitherto positive (negative) returns on winner (loser) stocks turning negative (positive).

[Conrad and Kaul \(1998\)](#), however, adopt the “rational view” that momentum profits (and that of other return-based trading strategies) are premia for risk – proxied in their study by securities’ return variances. Similarly, when the [Fama and French’s \(1993, 1996\)](#) 3-factor model is used as the rational pricing benchmark, [Jegadeesh and Titman \(2001\)](#) find that the return reversals are weak for large firms; evidence reminiscent of a similar characterization of [De Bondt and Thaler’s \(1985, 1987\)](#) contrarian portfolios. Another shared characteristic of contrarian and momentum portfolios is the observed seasonality of their evidenced excess returns; albeit positive for contrarian portfolios and negative for momentum portfolios. In [Jegadeesh and Titman \(1993\)](#), a significant portion of the lost momentum profits is in the month of January with losses averaging 7 percent. When this is compared with the 1.66 percent average return recorded in non-January months and the similar seasonality observed (in the opposite direction) for contrarian portfolios, it could be argued that the January effect is more than a passing phenomenon.

Explanations other than underreaction for price momentum have also been suggested (e.g., [Lewellen, 2002](#)). As opposed to underreaction to firm-specific news, [Lewellen \(2002\)](#) argues that excess covariance among stocks explain momentum effects observed in portfolios constituted based on size and B/M. Also, [Chan, Jegadeesh, and Lakonishok \(1996\)](#) attempt an explanation for short-term return persistence observed in [Jegadeesh and Titman \(1993\)](#) and other underreaction studies; especially with respect to the utility of six-month historical returns and earnings surprises (proxied by among others, the Standardized Unexpected Earnings (SUE)) in predicting *ex ante* returns. [Chan et al. \(1996\)](#) find an underreaction effect robust to market, size and value risks.

[Rouwenhorst \(1998\)](#) also corroborates the profitability of the momentum strategy using data from 12 European countries for the sixteen-year period of 1980 to 1995 to conduct out-of-

sample investigations of the profitability of relative strength strategies. The study presents evidence consistent with [Jegadeesh and Titman \(1993\)](#); with its winner portfolios outperforming the loser portfolios over one-year horizons in each of the twelve countries. The arbitrage momentum portfolio (W-L) earns an average 1 percent per month irrespective of firm size and market risk; but they observe stronger return persistence for smaller firms. Similarly, the returns are not in any way overwhelmed by commonly used asset pricing models. In fact, when the excess momentum portfolio returns are adjusted for market and size risk factors, they record alpha returns that are highly significant. For instance, when beta risk-adjusted alphas of 0.88 percent and -0.27 percent per month for the winner and loser portfolios respectively are further adjusted for risk related to size – proxied by [Fama and French's \(1996\)](#) SMB factor, the risk-adjusted return actually increases from 1.14 percent to 1.46 percent per month ([Rouwenhorst, 1998](#)).

[Moskowitz and Grinblatt \(1999\)](#) highlight the concentration risk inherent in individual stock momentum portfolios, which tend to be dominated by stocks from similar industries. Industry momentum strategies – long stocks from industries with stellar historical performance and short those from poor industries – however, outperform momentum portfolios constituted based on individual stock performance. This is in addition to diversifying away firm-specific risks that persist when highly correlated stocks from similar industries dominate the momentum portfolio. [Moskowitz and Grinblatt \(1999\)](#) argue that much of the profits recorded by individual stock momentum portfolios can be accounted for by industry momentum. Additionally, both strategies exhibit return behaviour commonalities over medium and long-term horizons consistent with return reversals evidenced in other momentum portfolios. Over short-term horizons, however, industry momentum portfolios clearly outperform individual stock ones, with the latter recording negative profits over one-month horizons, similar to the observation by [Jegadeesh \(1990\)](#).

2.6 Other thoughts in regard of Investor Reaction

In contrast to behavioural models by [Barberis et al. \(1998\)](#), [Daniel et al. \(1998\)](#) and [Hong and Stein \(1999\)](#), [Grinblatt and Han \(2005\)](#) refute the supposed predictive utility of historical returns. Instead, they attribute the profitability of the momentum strategy to delayed convergence of stock prices to fundamental values owing to the “disposition effect” – the tendency of investors to hold on to losers too long and sell winners too early ([Shefrin and Statman, 1985](#)). They regress weekly returns on lagged cumulative returns, logarithm of market capitalization, and average weekly turnover for stocks listed on the NYSE and AMEX. When they control for the potential capital gain, by including their capital gains overhang variable in the [Fama and MacBeth \(1973\)](#) type regression, the intermediate-horizon momentum profits hitherto recorded largely disappear; they suggest this evidence is a demonstration that historical returns have disutility in predicting [Jegadeesh and Titman \(1993\)](#) type momentum profits.

Return continuation and reversal persist still. Another attempt ([McLean, 2010](#)) at explaining their persistence suggests idiosyncratic risk and its associated costs might be what deter arbitrageurs from exploiting it away. Studies (e.g., [De Long, Shleifer, Summers, and Waldmann, 1990](#); [Shleifer and Vishny, 1990](#); et cetera) suggest cost-benefit trade-offs associated with exploiting some deviations from fundamental value might be a disincentive for arbitrageurs. [McLean \(2010\)](#) presents findings consistent with contentions that return reversals are price corrections ([De Bondt and Thaler, 1985, 1987](#); [Barberis et al., 1998](#); [Daniel et al., 1998](#); [Hong and Stein, 1999](#); et cetera).

Interestingly, however, [McLean \(2010\)](#) doesn’t find evidence that support the contention by [Barberis et al. \(1998\)](#); [Daniel et al. \(1998\)](#); and [Hong and Stein \(1999\)](#) that underreaction and overreaction have a causal relationship. Whereas, stocks that exhibit the strongest reversals are found in its highest idiosyncratic risk quintiles, it finds momentum stocks across all of its idiosyncratic risk quintiles; especially in quintiles for which reversals were not evidenced.

Other studies (e.g., [Grinblatt and Moskowitz, 2004](#)) also confirm the classical overreaction literature ([De Bondt and Thaler, 1985](#)) of the link between return reversals and the January effect. [Grinblatt and Moskowitz \(2004\)](#) find their 3-year contrarian portfolios are mostly profitable in the month of January and do not find similar seasonality in the momentum portfolios; evidence at variance with contemporary views (e.g., [Barberis et al., 1998](#); [Chan, 2003](#)) that underreaction and overreaction are sequential elements of the price discovery process. Instead, they opt for a tax avoidance explanation after examining the relationship between tax regimes and return autocorrelations.

Using the “Dow Jones Interactive Publications Library of past newspapers, periodicals and newswires”, [Chan \(2003\)](#) studies the reaction of stock prices to public but firm-specific news. In the study, winner and loser portfolios are formed based on returns *ex post* news specific to each stock; with the highest (lowest) return stocks put in the winner (loser) portfolio and held for a 36-month period. The study supports the classical ([De Bondt and Thaler, 1985, 1987](#); [Jegadeesh and Titman, 1993, 2001](#)) and contemporary ([Barberis et al., 1998](#); [Daniel et al., 1998](#); [Hong and Stein, 1999](#)) literature on overreaction and underreaction being contiguous elements of investor behaviour: Winners outperform losers over short to intermediate time horizons (typically 1 to 12 months) with reversals occurring over long-time horizons (typically from the thirteenth month post-portfolio formation).

In contrast to the predictions of the EMH that investors should not be able to earn abnormal profits based on public news, [Chan \(2003\)](#) finds that stock prices are not precipitously reflective of new public information; evidence that confirm that investors respond slowly to new information. In fact, the momentum portfolios do not experience any price drift without public news. Whereas winner and loser portfolios formed based on historical price movements alone (so-called “no-news stocks”) exhibit reversals in consonance with the negative time-series autocorrelation evidence in support of overreaction.

Furthermore, [Chiao and Hueng \(2005\)](#) find the overreaction effect robust to the three-factor model in the Japanese equity market. Similar to [Carhart’s \(1997\)](#) proposition of a fourth risk

factor to account for the empirical regularity observed for the momentum effect, [Chiao and Hueng \(2005\)](#) propose a “Loser Minus Winner” (LNW) factor for inclusion among the factors that explain the cross-section of returns; a “four-factor model.” They present evidence showing the model is robust to both Japanese and U.S data.

Much of the extant literature is dominated by U.S studies. There is increasing interest, however, in understanding how investors behave in other markets as hitherto closed but huge economies have opened up. A case in point is China. [Kang, Liu, and Ni \(2002\)](#) investigate the contrarian and momentum strategies in the Chinese equity market over the period: 1993 – 2000. They provide interesting insights on investor behaviour under regulatory and informational constraints. While both strategies are evidenced, the typical long-horizon contrarian strategy is a short-term phenomenon in the Chinese equity market. [Kang et al. \(2002\)](#) attribute this to the dominance of that market by individual investors who are forced to rely on rumours and historical price data to make investment decisions owing from the dearth of reliable information on stocks; circumstances that amplify the overreaction effect in the Chinese equity market.

2.7 Stock Market Seasonality

The January effect remains a conundrum. Using an equal-weighted index of NYSE prices, [Rozeff and Kinney \(1976\)](#) observe return outperformance for the calendar month of January for the period 1904 to 1974. On average, January returns outperform the other eleven months by 728.6%. That is, January average return was 3.48% and the other months averaged 0.42%. While [Rozeff and Kinney \(1976\)](#) do not seek to prove the observed seasonality, they proffer the tax-loss selling, accounting information and stochastic cash demand hypotheses as potential explanations.

[Schultz \(1985\)](#) juxtaposes pre-1917 returns data – the period prior to the introduction of the personal income tax in the United States – with those for the period 1918 – 1929. He didn’t find any evidence supporting a “January effect” in returns for the pre-1917 period, thereby showing

empirical support for the tax-loss selling hypothesis. This has not been consistent across markets (e.g., [Page and Way, 1992](#)), however, and has since been refuted for U.S. bourses ([Reinganum, 1983](#)). The tax-loss selling explanation for the turn-of-the-year effect has probably enjoyed prominence because of the dominance of tax concerns in investment decision-making in such countries as the U.S. and other highly integrated markets. The discovery of the effect in markets where tax considerations doesn't seem to be differential ([Kato and Schallheim, 1985](#); [Berges, McConnell, and Schlarbaum, 1984](#)), however, challenges the consistency of this prospective explanation.

Past attempts at explaining the seasonal anomaly include the tax-loss selling hypothesis ([Chan, 1986](#); [D'Mello, Fernis, and Hwang, 2003](#)), "window-dressing" by institutional investors ([Lakonishok, Shleifer, Thaler, and Vishny, 1991](#)), "data-snooping" ([Lo and Mackinlay, 1990](#); [Sullivan, Timmerman, and White, 1999](#)) and "parking the proceeds" ([Ritter, 1988](#)) explanations. Additionally, the supposition that the January effect is largely a small-firm phenomenon ([Lakonishok and Smidt, 1988](#); [Ritter, 1988](#); [Haug and Hirschey, 2006](#)) seems to be a popular view.

[Reinganum \(1983\)](#) makes a good attempt at bringing about some clarity on the linkages between tax-loss selling (candidate stocks for which are prior losers), the size effect and the January effect. After sorting stocks in ascending order of their prior 6-month performance, the worst performers ("losers") being the best tax-loss selling candidates and the best performers ("winners") being the worst tax-loss selling candidates, [Reinganum \(1983\)](#) forms market-value quintile portfolios, each of which is constituted of both losers and winners. Superior returns in January are still observed in the lowest market value quintile portfolios for winners (the worst potential tax-loss selling candidates); evidence suggestive of a size effect in January irrespective of tax-loss selling.

Additionally, [Haug and Hirschey \(2006\)](#) present evidence suggesting the January effect could still be considered a small cap phenomenon. They used value-weighted returns for the period

1802-2004 and equal-weighted returns for 1927-2004 and found the January effect to be prevalent in equal-weighted returns even after the passage of the Tax Reform Act of 1986 thereby also confirming earlier works (e.g., [Chan, 1986](#)) that the January effect cannot be explained by tax-loss selling. They also suggest a negative January effect for momentum stocks.

Using daily buy/sell orders of individual investors' accounts at a major U.S brokerage, [Ritter \(1988\)](#) finds that individual investors buy more securities than they sell in January and sell more than they buy in the prior December. [Ritter \(1988\)](#) generalizes that variations in this seasonal investor behaviour grossly explains the turn-of-the-year effect. It thus discounts the trading activities of institutional investors.

In contrast to [Reinganum \(1983\)](#), [D'Mello, Fernis, and Hwang \(2003\)](#) investigate the tax-loss selling hypothesis using 6-year data for firms across all sizes and control for factors (e.g., size) that have been found to explain the January seasonal in earlier studies (e.g., [Banz, 1981](#)). They discount the size and share price effects explanations for the January effect. Instead, they opine that the seasonal anomaly is a consequence of individual tax-loss selling at the end of the year and deferral of capital gains recognition to the beginning of the New Year. [D'Mello et al. \(2003\)](#) conclude thus following evidence of abnormal selling pressures in December for stocks that record significant losses during the year, selling activity that disappear in the next January and are replaced by abnormal selling of stocks with significant capital gains. They associate this behaviour with "capital-constrained" investors: individuals.

A comparison of trading patterns of individuals and institutions around the turn of the year suggests the January effect is primarily because of the trading patterns of individual investors; evidence not dissimilar to earlier studies by [Ritter \(1988\)](#) and [Sias and Starks \(1997\)](#). Thus, while institutional window dressing ([Lakonishok et al., 1991](#)) is plausible and probably accounts for some of the turn-of-the-year effect, it pales in comparison to individual trading behaviour in explaining the January effect ([D'Mello et al., 2003](#)).

[Lakonishok et al. \(1991\)](#) investigate the intuition that abnormal selling of loser stocks by institutional investors (e.g. pension managers) toward the end of the year is motivated by a desire to embellish year-end results and impress fund sponsors even when their rational thinking suggest otherwise. They look at the trading patterns of 769 equity pension funds and find behaviour that accentuate the momentum effect at the turn of the year when most of the funds dump loser stocks for winning ones. [Lakonishok et al \(1991\)](#) also observe that while institutional investors in general are contrarian, this behaviour is disproportionately pronounced around the turn-of-the-year as enhanced buying of long-trending loser stocks is also observed.

The tax-loss selling argument subsists still. [Kang, Pekkala, Polk, and Ribeiro \(2011\)](#) suggest an additional explanatory variable: interest rates. They argue that the difference in the tax credit or savings between a tax-loss sale on the last trading day in a prior December and the first trading day in the subsequent January is differential by the interest rate – since the latter tax credit would not be got in another twelve months and thus a discounted value becomes the proxy for the potential gain to be had. This is counterintuitive, however, for it is unlikely that rationality would suggest delaying the acquisition of a benefit today, for one lesser – at least in real terms – one year thence. Moreover, the question is whether the positive abnormal return of losers (or high tax-selling premium stocks) in January is due to tax-loss selling. Delaying the sale of such stocks – which is the only basis for the utility of interest rates in determining seasonality in the argument espoused in [Kang et al. \(2011\)](#) – does not explain the preponderance of purchase of such stocks at the beginning of the year.

The utility of interest rates is lost in deciding on loser stock purchases in January for the potential tax credit benefit at the end of the year when stock price volatility and prediction limitations are considered. It certainly cannot be supposed that a high tax-selling premium stock would remain static until the investor decides to sell it one year after the initial discovery of the tax-selling premium. In fact, top-percentile loser stocks (or very high tax-selling premium

stocks) have been consistently found to reverse and rise to record highs as early as the first trading week of January (De Bondt and Thaler, 1985 and 1987; Reinganum, 1983; et cetera).

However, Robins, E.M., Sandler, M., and Durand, F. (1999) find the January effect in the Johannesburg Stock Exchange value-weighted industrial index. In addition to a value-weighted index being biased towards large-caps, the JSE industrial index consists mostly of them. The findings by Robins et al (1999) contradict numerous studies (e.g., Keim, 1983; Blume and Stambaugh, 1983; Ritter, 1988) that link the January effect to small firms and the trading activities of individual investors, being as it is that the JSE is dominated by institutional investors (Robins et al., 1999). This January-Size effect continues to be a popular view, however.

Heston and Sadka (2010) consider data from 14 countries outside the U.S. in their investigation of seasonality in the cross-section of stock returns. They form momentum portfolios based on past excess market returns and find seasonality that is not peculiar to the month of January, in contrast to earlier momentum effect studies (e.g., Jegadeesh and Titman, 1993). Similarly, their findings are robust to size, β and value risks, suggesting some other factor is responsible for the regularity. Since the observed momentum and seasonal effects are not found to be highly correlated across countries, it also eliminates global systematic risk as a potential explanation. They conjecture that potential explanations would probably be related to behavioural or institutional factors.

Ng and Wang (2004) investigate the relationship between institutional trading and the turn-of-the-year effect. Firstly, however, they confirm the turn-of-the-year effect using data from December 1986 to January 1999 and find evidence consistent with earlier findings (e.g., De Bondt and Thaler, 1985, 1987; Schwert, 2001; et cetera): the January effect is more pronounced in small stocks relative to large stocks (3.7% for the small stocks and -1.3% for the large stocks), with the extreme losers in the stratum outperforming the winner types on a consistent basis. While the winner small stocks also display some marginal seasonality, Ng and Wang (2004) do not find this to be persistent across all sub-periods, however. Additionally, the difference

between the returns earned by the small-size stock portfolios in the last ten days of December of the prior year and that earned in the first ten days of January of the subsequent year were positive and statistically significant throughout the period investigated, with average returns ranging from 5.9% to 9.2%.

The focus on institutional investors by [Ng and Wang \(2004\)](#) is premised on evidence (by [Gompers and Metrick, 2001](#)) that their ownership of U.S equities had risen from 27.6% in 1980 to more than 50% in 1998. Studies of the turn-of-the-year effect have sought to investigate the investing behavior of individuals (e.g., [Ritter, 1988](#); [D'Mello et al., 2003](#)) and institutions (e.g., [Lakonishok et al., 1991](#)) with the reckoning that they might provide insights on the underlying determinants of the turn-of-the-year effect. [Ng and Wang \(2004\)](#) find that institutions sell (buy) loser (winner) stocks across all size quintiles towards the end of the year, an activity that could be interpreted as a momentum strategy or window-dressing in anticipation of statutory disclosures. While they opt for the window-dressing interpretation, they do not present evidence that suggest that it couldn't be a deliberate momentum strategy as well.

[Cooper, McConnel and Ovtchinnikov \(2006\)](#) examine whether January returns have predictive utility for returns to be expected in the remaining months of the year, a so-called "Other January effect." Using data spanning the period 1940 to 2003, they present evidence in support of their intuition (or "financial market street-lore" as they put it). For years in which January returns were positive, [Cooper et al. \(2006\)](#) find that returns average a positive 14.8 percent for the rest of the year. Conversely, for negative January returns, they find the next eleven months for the period considered averaged 2.92%. They also find the effect robust to [Fama and French's \(1993 and 1996\)](#) three-factor model, especially with respect to SMB and HML. In any case, the issue of relevance here is that investor behaviour is distinctive in the month of January.

Return has also been found to be differential in other months for some markets. For example, [Claessens, Dasgupta, and Glen \(1995\)](#) found the months of March and June to be statistically

differential with respect to return behaviour on the Nigerian bourse. A later study, [Alagidede \(2008\)](#), found returns in the months of February and June to be statistically different from those of other months of the year as well; with June recording the highest return of all the months. The February effect has also been documented for China as well ([Wang, Ojiako, and Wang, 2013](#)).

2.8 Summary Insights from the literature

Thus far, it has been established that both short-term return persistence and long-term reversals share a commonality: they are more pronounced in the month of January. Additionally, behavioural models ([Barberis et al., 1998](#); [Daniel et al., 1998](#); [Hong and Stein, 1999](#)) show both phenomena are not disparate, albeit relying on different concepts from the psychology literature ranging from conservatism ([Edwards, 1968](#)) and self-attribution ([De Long, Shleifer, Summers, and Waldmann, 1991](#)) for underreaction, to representativeness ([Tversky and Kahneman, 1974](#)) and overconfidence ([Odean, 1998](#)) for overreaction.

Most attempts at explaining the seasonality of investor overreaction since [De Bondt and Thaler \(1987\)](#) are related to taxes (e.g., [Grinblatt and Moskowitz, 2004](#); [George and Hwang, 2007](#)). However, other studies (e.g., [Page and Way, 1992](#); [Cubbin et al., 2006](#)) find the January seasonal in markets (e.g., South Africa) where tax considerations are not differential, evidence that the tax explanation is not a robust one. Thus, the reason why return reversals occur mostly in the calendar month of January remains an open question.

What seems to be consistent in the literature are as follows. Buying pressure in January is biased towards undervalued stocks in the prior December, tax-loss selling (though not an exhaustive explanation) seem a motivation for some investors to sell losing stocks in December in markets such as the United States ([Schultz, 1985](#); [D'Mello et al., 2003](#); [Ng and Wang, 2004](#); [Kang et al., 2011](#)), even though [Reinganum \(1983\)](#) and [Haug and Hirschey \(2006\)](#) refute this, and for other reasons in some ([Kato and Schallheim, 1985](#); [Berges et al., 1984](#)). Tax-loss selling doesn't explain, however, the subsequent buying activity in January.

Other alternative explanations (Lakonishok et al., 1991; Lo and MacKinlay, 1990; Sullivan et al., 1999; D'Mello et al., 2003; Ng and Wang, 2004; et cetera) have not been found to be exhaustive either since the January effect continues to persist irrespective of investor type or any supposed statistical bias. Additionally, the observed seasonality in winner-loser portfolios, with loser stocks or hitherto undervalued stocks earning significant positive risk-adjusted returns in January (De Bondt and Thaler, 1985; Jegadeesh, 1990; et cetera) continues to be unexplained by existing theory (De Bondt and Thaler, 1987). The subsequent overreaction literature (Chan, 2003; Grinblatt and Moskowitz, 2004; George and Hwang, 2007; Lin and Swanson, 2010) do not provide any novel explanations for the anomaly, either.

3. METHODOLOGY

The philosophical underpinning of this study is post-positivist. A claim is made in the form of a hypothesis, data is collected and analysed, and conclusion(s) are made to reject or fail to reject the hypothesis. Post-positivism represents new thinking about the scientific method and is based on the recognition that while inquiry should be objective and based on evidence, conclusions thereof should by no means be considered absolute. It recognizes that knowledge continually evolves and such a thing as orthodoxy is a fallacy. Thus, extant theory in regard of investor overreaction is first established using out-of-sample data. Thereafter, a claim is made in regard of some of the unanswered questions raised in past studies (Creswell, 2009).

This quantitative research approach relies on data from markets outside of the U.S to control for the potential sample bias that perhaps dominate the finance literature. It is recognized here that new thinking evidenced in this study would be greatly impaired if it is not found to be consistent. This recognition informs the adoption by this study, of the quantitative method for its high standards with respect to validity and reliability of research work.

The research design relies on the past works of De Bondt and Thaler (1985, 1987), Ritter (1988), Conrad and Kaul (1993) and Lee and Swaminathan (2000). However, nuances that allow the specific question(s) of interest to be investigated are also introduced; as the objective is to understand the role of investor sentiments in explaining the seasonality and intensity of investor reaction. The intuitive congruity of return and investor sentiments is also investigated especially as the literature (e.g., Lee and Swaminathan, 2000) suggests they are governed by the same market dynamics. Thus, the design uses De Bondt and Thaler's (1985) type loser and winner portfolios to investigate whether share turnover ratio – the proxy for investor sentiment used – follows a similar post-formation pattern as the return from these portfolios.

3.1 Research design

It is conjectured that investor sentiments have explanatory power for the cross-section of stock returns and are differential at the turn of the year. The intuition is that these sentiments explain January loser reversals documented in [De Bondt and Thaler \(1985, 1987\)](#). If this intuition is to be vindicated, then investor sentiment would behave similarly as return in the event of an overreaction effect and accompanying January effect.

[Conrad and Kaul \(1993:39\)](#) aptly posit the overreaction hypothesis as follows: “stock prices take temporary swings from their fundamental values due to waves of optimism and pessimism.” Additionally, [Baker and Wurgler \(2006:1649\)](#) define investor sentiment as “optimism and pessimism about stocks in general” and use share turnover as one of the proxies for investor sentiment. Other proxies that have been used are the “closed-end fund discount, the number and average first-day returns on IPOs, the equity shares in new issues, and the dividend premium” ([Baker and Wurgler 2006:1655](#)).

[Ritter \(1988\)](#) uses daily buy/sell orders of individual investors’ accounts at a major U.S brokerage firm to test its “parking-the-proceeds” hypothesis for the January effect¹. In this research, share turnover ratio (ST) – defined as the ratio of daily trading volume for a stock to its number of shares outstanding – is used as the proxy for investor sentiment; and nonparametric ANOVA models are used to determine whether they are differential separately across loser/winner quintile portfolios and months of the year, especially the month of January. It is worth noting at this point that other proxies of investor sentiment could not be used in this study because of unavailability of rich data needed to compute them.

¹ [Ritter \(1988\)](#) finds that individual investors buy more securities than they sell in January and sell more than they buy in the prior December. The paper generalizes that variations in this seasonal investor behaviour grossly explains the turn-of-the-year effect.

Share turnover has been found to be seasonal. [Eleswarapu and Reinganum \(1993:385\)](#) use share turnover as a proxy for liquidity and present evidence showing that the “liquidity premium is reliably positive only during the month of January.” However, they do not explain why the liquidity effect is limited to January. [Lee and Swaminathan \(2000\)](#) refute the liquidity hypothesis for the explanatory power of share turnover for the momentum effect observed in their study. They find minimal correlation between share turnover and common liquidity proxies like firm size, stock price and relative spread. They insist their finding is evidence that share turnover proxies for something more than just liquidity. This study conjectures that it is a proxy for investor sentiment.

This study draws on the pioneering work in regard of stock market overreaction by [De Bondt and Thaler \(1985\)](#) for constructing winner and loser portfolios.

[De Bondt and Thaler’s \(1985\)](#) overreaction hypothesis predicts that:

$$ACAR_w(k) < 0$$

$$ACAR_L(k) > 0$$

$$DACAR(k) > 0$$

Where

k = 12, 24, and 36 months

L = Loser portfolio

W = Winner portfolio

ACAR = Average cumulative abnormal Return

DACAR = Difference in average cumulative abnormal returns of loser and winner portfolios

Conrad and Kaul (1993) raise methodological questions about De Bondt and Thaler's (1985 and 1987) return calculation approach and suggest bias(es) that potentially weaken generalizations in past studies based on the overreaction hypothesis hitherto. Their methodological variation necessitates De Bondt and Thaler's (1985) overreaction hypothesis to be restated as follows:

$$AHPAR_W(k) < 0$$

$$AHPAR_L(k) > 0$$

$$DAHPAR(k) > 0$$

Where

AHPAR = Average holding period abnormal return

DACAR = Difference in average holding period abnormal return for loser and winner portfolios

And k, L and W are the same as defined in De Bondt and Thaler's (1985) model.

In this study, average holding period returns for securities listed on the NSE and JSE are separately ranked in descending order and put in loser/winner quintile portfolios. These are then evaluated over 12-, 24- and 36-month holding periods.

Lee and Swaminathan (2000) present evidence showing underreaction and overreaction are linked by trading volume proxied by the share turnover ratio. They create momentum portfolios based on historical trading volume that exhibit intermediate-horizon return continuation along the lines of Jegadeesh and Titman (1993) and long-horizon return reversal as predicted by De Bondt and Thaler (1985). What is particularly interesting in Lee and Swaminathan (2000) is their assertion about the utility of historical trading volume in predicting the timing of return reversals. Incidentally, Campbell, Grossman and Wang (1993) and Blume, Easley and O'Hara (1994) provide theoretical evidence that show strong linkages between stock returns and trading volume.

After separately ranking stocks based on their historical returns and trading volume, [Lee and Swaminathan \(2000\)](#) form thirty “price momentum-volume portfolios” that consist of stocks common to strata in both rankings. These portfolios are then held for varying periods ranging from three months to five years. The arbitrage momentum portfolio, one that is long extreme decile winners and short extreme decile losers, is profitable in the first year with returns ranging from 10.62 percent to 12.70 percent per year. The strong performance unravels, however, in the fourth year and endures to the fifth whereby the portfolio records negative returns irrespective of the formation period. This is evidence consistent with the predictions of [De Bondt and Thaler’s \(1985\)](#) overreaction hypothesis. Additionally, the extreme winner and loser portfolios share a commonality: they are characterized by high trading volume stocks. This is at variance with the liquidity effect argument. This study draws on methodological insights from [De Bondt and Thaler \(1985\)](#) and [Lee and Swaminathan \(2000\)](#).

[Ritter \(1988\)](#) regress small-firm excess stock returns on daily buy/sell ratios (BSRs) of individual investors during the first two trading weeks of the year in January and finds that it has explanatory power for the January effect. While it doesn’t investigate the underlying causes of such investor behaviour, it attributes the anomaly to tax-loss selling in December. The study conjectures that individual investors use the proceeds to procure small-firm stocks in January. Ritter’s study comes close to the contemplation in this study about the intuitive appeal of a relationship between return and investor sentiments.

The JSE and NSE are the two largest equity markets in Sub-Saharan Africa. This study focuses on the two bourses because they are the largest by market capitalization and yet have sharp differences in infrastructure, microstructure and investor characteristics. In regard of the JSE, an obviously more developed equity market relative to the NSE, its flexible tax year and dominance by institutional investors ([Robins et al., 1999](#)) provide opportunities to explore unresolved questions raised in U.S studies (discussed earlier) as to whether tax-loss selling and individual investor behaviour explain investor overreaction and the January effect.

Incidentally, [Page and Way \(1992\)](#) document results consistent with the overreaction hypothesis and thus inconsistent with the weak-form EMH for the South African equity market. They observe a January effect similar to that evidenced on the New York Stock Exchange by [De Bondt and Thaler \(1985\)](#). Their findings call into question the hypothesis that positive loser excess returns in January is due to tax loss selling as South African companies are free to choose their tax year ends. While other JSE overreaction studies ([Cubbin, Eidne, Firer, and Gilbert, 2006](#); [Venter, 2009](#)) confirm [Page and Way's \(1992\)](#) findings of overreaction in the South African equity market albeit using different methodologies – e.g., [Cubbin et al. \(2006\)](#) use P/E ratios to rank portfolios and in the case of [Venter \(2009\)](#) focus on intra-day trading behaviour – they are not exactly comparable with that pioneer South African overreaction study. Thus, one such study that adopts a methodology consistent with the [De Bondt and Thaler \(1985\)](#) methodology used in [Page and Way \(1992\)](#) is apt.

Furthermore, existing evidence for the Nigerian equity market ([Olowe, 1999](#); [Tijjani et al., 2009](#); et cetera) suggests it is weak-form efficient. Most of these studies, however, were autocorrelation tests. Thus, there is a dearth of studies of trading-rule efficiency tests like in this study. Other drawbacks in these prior studies include small sample sizes: [Olowe \(1999\)](#) use fifty-nine (59) randomly selected securities as its sample and [Tijjani et al. \(2009\)](#) use sixty-nine (69). Additionally, they do not include observations beyond the year 2005, a period for which the Nigerian bourse experienced marked activity. Also, studies of other price-limit regulated equity markets (e.g., [Lin and Swanson, 2010](#)) show contrarian strategies earn superior returns, evidence in support of overreaction and converse to the efficient market argument. The intuition of this study, therefore, is that the Nigerian equity market is not likely to be efficient as suggested by the existing Nigerian efficiency literature (e.g., [Tijjani et al., 2009](#); [Okpara, 2010](#)).

In Nigeria, individuals and firms could hitherto file their tax returns at any time of the year. However, Nigerian banks adopted a common year-end of December in 2011 as per regulations. Although this study includes 2011 data for Nigeria, it is not considered material enough to alter the results. In South Africa, most listed firms are large-caps, individual investors' tax year ends

in February and there is no statutory financial year-end for firms (Page and Way, 1992). A study of both bourses thus helps control for the size and tax-loss selling effects. These are characteristics, which in tandem with the research design help control for potential biases.

3.2 Portfolio formation

Using the methodology of De Bondt and Thaler (1985), loser (winner) portfolios are formed by using stocks that record the lowest (highest) returns over 1-, 2-, and 3-year horizons. Trading volume by itself does not give an indication on the direction of returns. It only becomes meaningful when juxtaposed with return performance as “stock returns and trading volume are jointly determined by the same market dynamics and are inextricably linked in theory” (Lee and Swaminathan, 2000:2017). That juxtaposition is a major thrust of this study.

While mean reversion has been evidenced on the JSE over short- and long-term horizons (Page and Way, 1992; Venter, 2009; Cubbin et al., 2006), it is not the case for the Nigerian Stock Exchange. Thus, the existence of the phenomenon on the NSE would have to be established. Having already been observed to occur on the JSE, investor overreaction would again be investigated using now available data for periods not included in prior studies – Cubbin et al. (2006) use a 1983 to 2005 dataset. It would also provide insights on whether it persists in the South African equity market.

To form the loser and winner portfolios and thereafter measure their performance, returns are computed for each security (or portfolio) as follows:

$$R_{j,t} = (P_{j,t} - P_{j,t-1}) / (P_{j,t-1}) \quad (3.1)$$

$$U_{j,t} = R_{j,t} - R_{m,t} \quad (3.2)$$

$$AR_{p,t} = 1/n \sum U_{j,t} \quad (3.3)$$

$$AHPAR_p = 1/m \sum AR_{p,t} \quad (3.4)$$

Where:

$R_{j,t}$ = monthly return for stock j

$U_{j,t}$ = monthly residual return for stock j

$AR_{p,t}$ = abnormal return of portfolio p over month t

$AHPAR_p$ = average holding period abnormal return of portfolio p over period k

$R_{m,t}$ = market return over month t

$P_{j,t}$ = closing price of stock j in month t

$P_{j,t-1}$ = closing price of stock j in month t-1

$t = 1, 2, \dots, m$

n = number of securities in the loser (or winner) portfolio, and

m = number of months in holding period

Share turnover ratios are computed for each security (or portfolio) as follows:

$$ST_{j,t} = V_{j,t} / N_{j,t} \quad (3.5)$$

$$ST_{p,t} = 1/n \sum ST_{j,t} \quad (3.6)$$

$$AHPST_p = 1/m \sum ST_{p,t} \quad (3.7)$$

Where:

$ST_{j,t}$ = share turnover ratio for security j over month t

$ST_{p,t}$ = share turnover ratio of portfolio p over month t

$AHPST_p$ = average holding period share turnover ratio of portfolio p

$V_{j,t}$ = average trading volume of security j over month t

$N_{j,t}$ = average number of shares outstanding of security j over month t

n = number of securities in the loser (or winner) portfolio

m = number of months in holding period

Thus, relevant variables for which data are collected are as follows:

- Daily closing value of the JSE and NSE All Share Index at closing for each day
- Daily closing price for each security
- Daily volume traded for each security
- Number of shares outstanding

JSE data was sourced from the McGregorBFA database via the Library at the Wits Business School and NSE data from a member firm of the Nigerian Stock Exchange. Data was also sourced from Thomson Reuters Datastream to check for accuracy and ensure consistency. Securities in each of the JSE and NSE samples had their monthly excess market returns (ARs) averaged for the pre-formation period, which ranged from one to three years, to determine whether it was a loser or winner security. They were thereafter ranked and divided into five (5) quintiles with the top quintile performers put into the extreme winner portfolio, P1, the lowest quintile performers put into the extreme loser portfolio, P5, and the remainder put in the other

three portfolios: P2, the second winner portfolio, P3, the intermediate portfolio, and P4, the second loser portfolio. Since the goal is also to investigate whether investor sentiment is congruous with return, the share turnover ratios (STs) of the securities are also observed over these post-formation periods.

As at the end of 2011, there were about 140 securities listed on the JSE, a much lower figure to the 186 listed securities on the bourse in 2002. The sample criterion adopted is that securities be listed on the bourse for the entire period of 2002-2011. Consequently, 75 securities were adopted for the study. From this 75-listed securities' sample, nine 1-year, seven 2-year, and five 3-year overlapping quintile loser-winner portfolios were formed with each one having fifteen securities. For the NSE sample, nine 1-year, seven 2-year, and five 3-year overlapping quintile loser-winner portfolios were formed with each one having 16 securities except the extreme loser portfolio, P5 which had 14 constituent securities.

3.3 Comments on data analysis method

The datasets are largely nonstationary and not normally distributed (see Tables 1 and 2). This is not entirely surprising as the normality assumption "in reality does not hold." ([Al-Khazali 2014:159](#)). Thus, the non-parametric Kruskal-Wallis One-Way Analysis of Variance (ANOVA) on Ranks test is used as the primary analytical tool in deciding whether to reject or not reject the null hypotheses. The distribution-free multiple comparison Kruskal-Wallis Z (Dunn's) test is used to determine which of the portfolios (or months) have residual returns (or share turnover ratios) that are differential.

Table 1: Results of normality and stationarity tests for the JSE datasets

Assumption [Decision (0.05)]	JSE average holding period abnormal returns (AHPARs)	JSE monthly abnormal returns (ARs)	JSE average holding period share turnover ratios (AHPSTs)	JSE monthly share turnover ratios (STs)
Skewness normality of residuals	Reject	Reject	Reject	Reject
Kurtosis normality of residuals	Reject	Reject	Reject	Reject
Omnibus normality of residuals	Reject	Reject	Reject	Reject
Modified-Levene Equal Variance Test	Reject	Reject	Accept	Accept

Source: NCSS

Table 2: Results of normality and stationarity tests for the NSE datasets

Assumption [Decision (0.05)]	NSE average holding period abnormal returns (AHPARs)	NSE monthly abnormal returns (ARs)	NSE average holding period share turnover ratios (STs)	NSE monthly share turnover ratios (STs)
Skewness normality of residuals	Reject	Reject	Reject	Reject
Kurtosis normality of residuals	Reject	Reject	Reject	Reject
Omnibus normality of residuals	Reject	Reject	Reject	Reject
Modified-Levene Equal Variance Test	Accept	Reject	Reject	Accept

Source: NCSS

The use of the nonparametric Kruskal-Wallis One-Way ANOVA on Ranks test to determine whether the differences in the values of the variables of interest for the study's quintile portfolios (or calendar months) are significant is consistent with earlier overreaction and/or seasonality studies (e.g., [Lee, 1992](#); [Alford and Guffey, 1996](#); [Ko, 1998](#); [Kunkel et al., 2003](#); et cetera). [Kunkel et al. \(2003\)](#) used the nonparametric Wilcoxon Signed Rank test, which like the Kruskal-Wallis One-Way ANOVA on Ranks, tests for differences in the median values of the relevant group variable(s). The Kruskal-Wallis ANOVA test has also been argued to be more robust than the One-Way ANOVA in events of parametric assumption violations ([Sprenst, 1989](#)).

To ensure consistency, the non-parametric multiple comparison Kruskal-Wallis Z (Dunn's) test is used to determine whether the differences between the residual returns (or share turnover ratios) of the arbitrage loser-winner portfolios are significant. The Dunn's test is a multiple comparison procedure that does not require the datasets to be normally distributed.

4. RESULTS AND FINDINGS

4.1 Overview

As a guide to this important chapter, the reader is given a quick overview of key results documented from the analyses. In line with the intuition that motivated the study, evidence of overreaction and seasonality are found on the Nigerian Stock Exchange (NSE). For the Johannesburg Stock Exchange (JSE), no evidence of overreaction is found. Seasonality is observed on the JSE, however. Thus, inefficiencies occur in both markets. In subsequent sections, the results are discussed in greater detail.

4.2 Findings of tests for investor overreaction and seasonality on the NSE

Test results for the NSE residual return dataset suggests there is an overreaction effect on the Nigerian Stock Exchange. The extreme loser portfolio, P5 had the highest average holding period abnormal return (AHPAR) of 7.1%, outperforming the corresponding winner portfolio, P1 (AHPAR of 3.7%), by 3.4 percentage points. And this difference was found to be statistically significant.

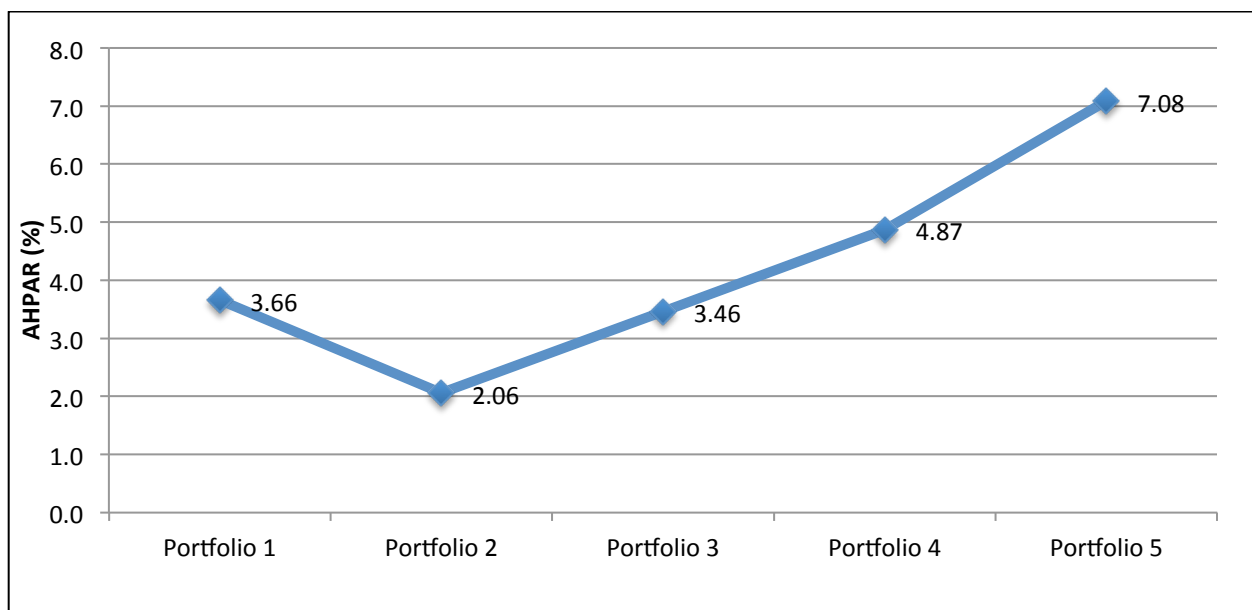


Figure 5: Means Plot of Average Holding Period Abnormal Returns (AHPARs) for NSE Portfolios

The Kruskal-Wallis One-Way ANOVA on Ranks test finds that at least two of the quintile portfolios have median AHPARs that are statistically different. It finds this to be case when the test is corrected for ties and otherwise. As can be seen in Table 3 below, the probability levels of the Chi-Square (H) values were lower than the alpha level of 0.05, pointing to statistical significance. Thus, the null hypothesis that there are no statistically significant return differences between the NSE loser-winner portfolios is rejected.

Table 3: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for NSE AHPARs

Method	DF	Chi-Square (H)	Prob Level	Decision (0.05)
Not Corrected for Ties	4	13.32	0.01	Reject H0
Corrected for Ties	4	13.32	0.01	Reject H0

Source: NCSS; Number Sets of Ties = 180, Multiplicity Factor = 1,080

To determine which of the NSE quintile portfolios are statistically different from each other, the similarly nonparametric Kruskal-Wallis Multiple Comparison Z-Value test (Dunn's test) was employed. As can be seen in Table 4 below, the z-value of 2.02 when the AHPARs of the extreme loser (P5) and winner portfolios (P1) are compared is greater than the threshold z-value of 1.96 for statistical significance at a 95% confidence level. This confirms the positive difference (3.4%) in the residual returns of the loser-winner arbitrage (P5-P1) portfolios as statistically significant and evidence of overreaction on the NSE.

Table 4: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for NSE portfolios' average holding period abnormal returns (AHPARs)

AHPAR	1	2	3	4	5
1	0.00	1.48	0.63	0.13	2.02*
2	1.48	0.00	0.86	1.61	3.50**
3	0.63	0.86	0.00	0.75	2.64**
4	0.13	1.61	0.75	0.00	1.89
5	2.02*	3.50**	2.64**	1.89	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

Additionally, the study investigates whether investor sentiment is differential between the quintile portfolios; especially the extreme loser and winner portfolios, P5 and P1. This is found to be the case. The positive difference between the AHPSTs for P5 and P1 (0.013%) is found to be statistically significant, based on the study's findings. This supports the observed overreaction effect found with respect to return residuals (AHPARs).

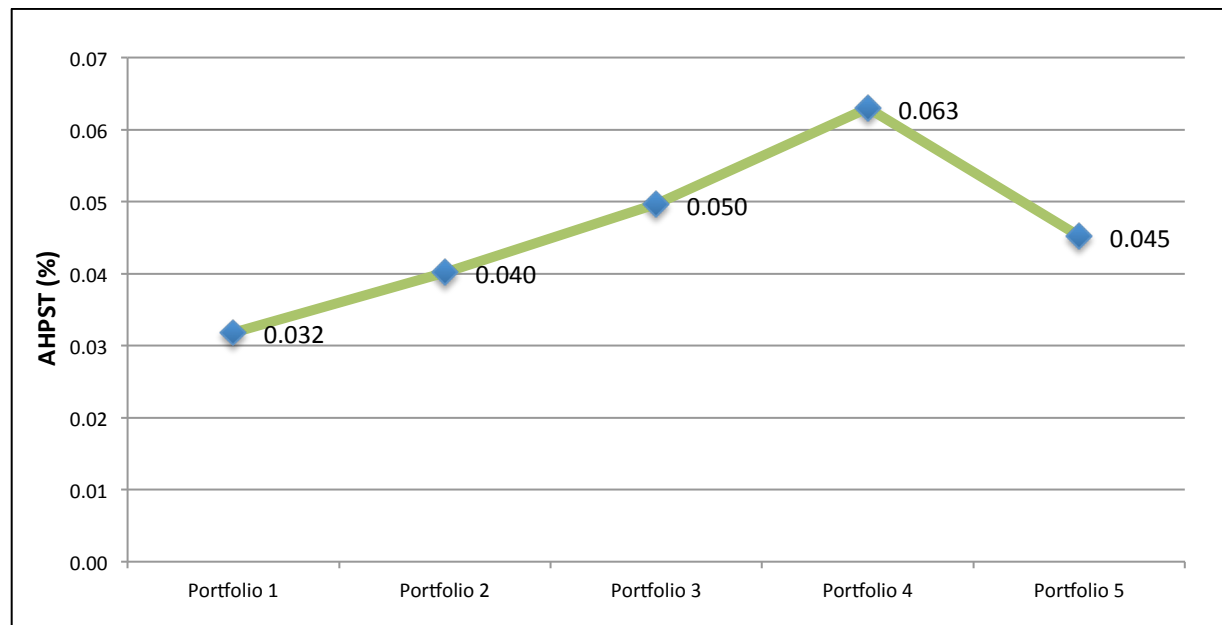


Figure 6: Means Plot of Average Holding Period Share Turnover Ratios (AHPSTs) for NSE Portfolios

As can be seen in Table 5, the Kruskal-Wallis H-statistic has a value of 63.95 and probability level of zero; both for when the test is corrected for ties or otherwise. It thus finds that at least

two of the quintile portfolios have median AHPSTs that are different and rejects the null hypothesis that all the NSE quintile portfolios have equal median AHPSTs.

Table 5: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for NSE Portfolios' AHPSTs

Method	DF	Chi-Square (H)	Prob Level	Decision (0.05)
Not Corrected for Ties	4	63.95	0.00	Reject H0
Corrected for Ties	4	63.95	0.00	Reject H0

Source: NCSS; Number Sets of Ties = 240, Multiplicity Factor = 1,440

With a Dunn's test Z-value of 7.95, the difference between the investor sentiment measure (AHPST) of the extreme loser and winner NSE portfolios (P5-P1) is statistically significant at the 95% and 99% confidence levels (see Table 6).

Table 6: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for NSE Portfolios' AHPSTs

AHPST	1	2	3	4	5
1	0.00	3.83**	4.56**	4.44**	7.95**
2	3.83**	0.00	0.73	0.61	4.11**
3	4.56**	0.73	0.00	0.12	3.39**
4	4.44**	0.61	0.12	0.00	3.51**
5	7.95**	4.11**	3.39**	3.51**	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

The observed overreaction effect on the NSE is accompanied by seasonality. When the monthly portfolio abnormal returns (ARs) are analysed, at least two calendar months are found to have median ARs that are statistically different. As can be seen in the Table 7 below, the H statistic has a value of 241.02 with a probability level of zero. As the probability level of the statistic is lower than the alpha level of 0.05, the null hypothesis that all the portfolios' median monthly ARs are not any different is rejected. This is evidence of seasonality on the NSE.

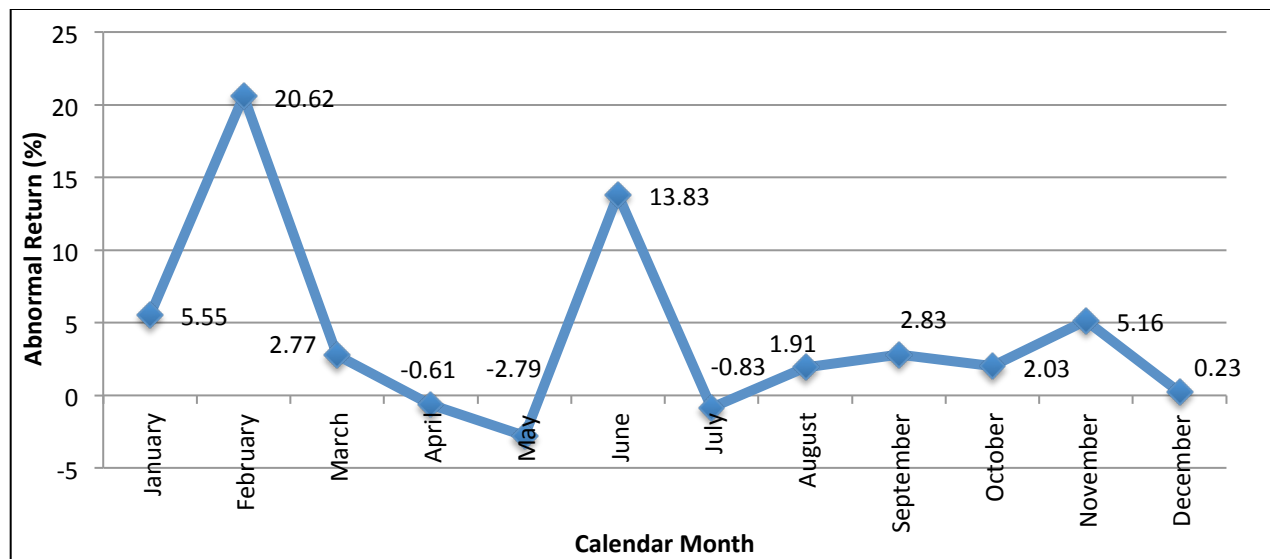


Figure 7: Means Plot of monthly abnormal returns (ARs) for NSE Portfolios

Table 7: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for NSE Portfolios' Monthly Abnormal Returns (ARs)

Method	DF	Chi-Square (H)	Prob Level	Decision (0.05)
Not Corrected for Ties	11	241.02	0	Reject H0
Corrected for Ties	11	241.02	0	Reject H0

Source: NCSS; Number Sets of Ties = 180, Multiplicity Factor = 1,080

Judging from Figure 7, it is clear that there is a distinctive increase in the return performance of the study's quintile portfolios at the beginning of the year. Monthly ARs for NSE loser-winner portfolios rise significantly in January (5.6%) relative to December (0.2%). The differences between the months are also statistically significant. Although NSE monthly ARs rise even higher in February to 20.6% (the highest point of all the calendar months), the Dunn's test does not find the returns of the months of January and February to be any different from each other (see Table 8). This study thus finds a January effect associated with the observed overreaction effect on the NSE.

Table 8: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for NSE Portfolios' Monthly Abnormal Returns (ARs)

AHPAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.00	0.99	2.43*	7.44**	10.10**	4.65**	8.51**	2.70**	1.38	3.55**	2.28*	7.54**
Feb	0.99	0.00	1.44	6.45**	9.11**	3.67**	7.52**	1.72	0.39	2.56*	1.30	6.55**
Mar	2.43*	1.44	0.00	5.01**	7.67**	2.23*	6.08**	0.28	1.05	1.12	0.14	5.11**
Apr	7.44**	6.45**	5.01**	0.00	2.66**	2.78**	1.07	4.73**	6.06**	3.89**	5.15**	0.10
May	10.10**	9.11**	7.67**	2.66**	0.00	5.45**	1.59	7.40**	8.72**	6.55**	7.82**	2.56*
Jun	4.65**	3.67**	2.23*	2.78**	5.45**	0.00	3.85**	1.95	3.28**	1.11	2.37*	2.89**
Jul	8.51**	7.52**	6.08**	1.07	1.59	3.85**	0.00	5.80**	7.13**	4.96**	6.22**	0.97
Aug	2.70**	1.72	0.28	4.73**	7.40**	1.95	5.80**	0.00	1.33	0.85	0.42	4.84**
Sep	1.38	0.39	1.05	6.06**	8.72**	3.28**	7.13**	1.33	0.00	2.17*	0.91	6.16**
Oct	3.55**	2.56*	1.12	3.89**	6.55**	1.11	4.96**	0.85	2.17*	0.00	1.27	3.99**
Nov	2.28*	1.30	0.14	5.15**	7.82**	2.37*	6.22**	0.42	0.91	1.27	0.00	5.26**
Dec	7.54**	6.55**	5.11**	0.10	2.56*	2.89**	0.97	4.84**	6.16**	3.99**	5.26**	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

Apart from January, the months of April, May, and June are also found to be distinctive. Negative returns on average are observed in the Easter month of April (AR of -0.61%). Two months thereafter (May and June), an upward trend is observed as the portfolios return to profitability with AR of 13.8% in June. This is interpreted as a June Effect. A similar pattern is seen in December. Monthly AR that declines in December to 0.23% (from 5.2% in the preceding month) recovers in January (5.6%) before peaking in February. Thus, there are statistically significant positive return behaviours in the months of January and June on the NSE. The observed calendar effects are observed to be return recoveries over the course of one to two months after declines around epochs with public holidays. In the case of the January effect, the preceding epoch is Christmas (December 25). The June effect comes two months after the Easter celebrations (April 5).

To further investigate this phenomenon, the study looks at investor sentiment around these periods. For whether investor sentiment (ST) is differential across months on the NSE, the chi-square (H) has a value of 20.98 and probability level of 0.03; thus enabling the null hypothesis of equal medians to be rejected at the 95% confidence level. Investor sentiments between

January and December are distinctively different. The quintile NSE portfolios' return underperformance in December and stellar return performance in January is vindicated by the statistically significant differences in investor sentiments (STs) for the same months. When the NSE monthly share turnover ratios (STs) and abnormal returns (ARs) between January and February are contrasted, some congruity is observed. The observed increase in NSE portfolios' AR in February to 20.6% from 5.5% in January – albeit not statistically different – happens in tandem with a similar but statistically significant increase in monthly ST to 0.06% in February from 0.04% in the preceding month of January.

While both AR and ST trends are congruous for the subsequent months of March, April and May, the significant increase in excess return performance in June ("June effect") is not reflected by the investment sentiment measure as the monthly ST effectively continued to decline till July before picking up in August. Incidentally, NSE monthly AR trended in tandem with ST subsequently, between August and November. Thus, except for the months of June and December, return was largely congruous with investor sentiment on the NSE.

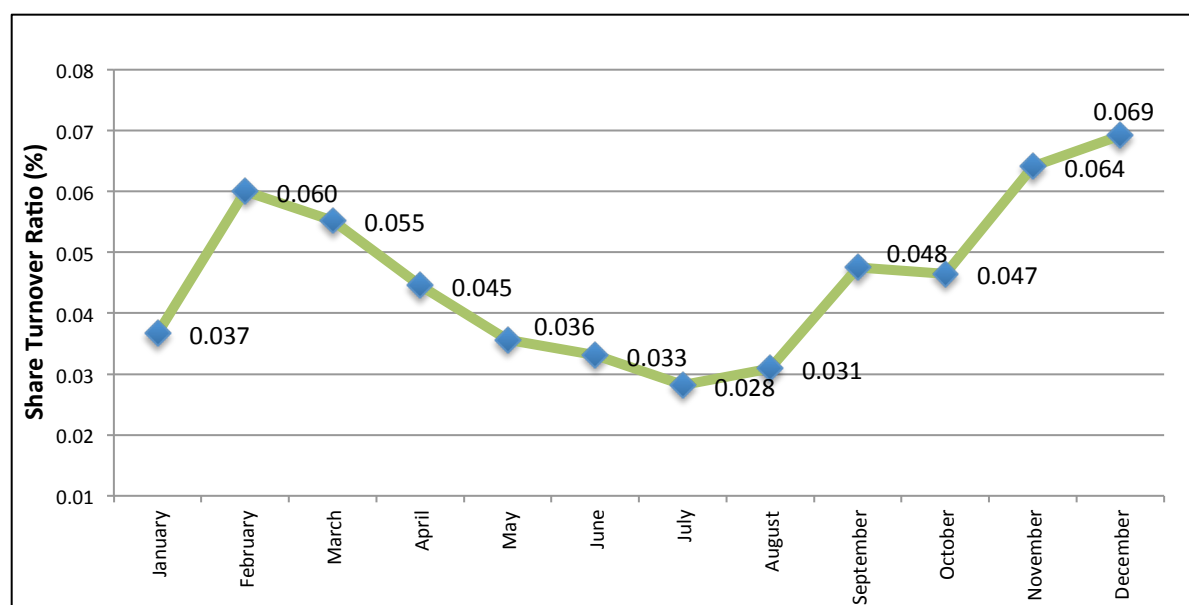


Figure 8: Means Plot of monthly share turnover ratios (STs) for NSE Portfolios

Table 9: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for NSE Portfolios' Monthly Share Turnover Ratios (STs)

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	20.98	0.03	Reject H0
Corrected for Ties	11	20.98	0.03	Reject H0

Source: NCSS; Number Sets of Ties = 240, Multiplicity Factor = 1,440

Table 10: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for NSE Portfolios' Monthly Share Turnover Ratios (STs)

AHPST	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.00	3.15**	2.05*	2.99**	2.27*	3.03**	2.32*	2.21*	3.90**	2.92**	3.41**	2.67**
Feb	3.15**	0.00	1.10	0.16	0.88	0.12	0.83	0.93	0.75	0.23	0.27	0.47
Mar	2.05*	1.10	0.00	0.94	0.22	0.98	0.28	0.17	1.85	0.87	1.37	0.63
Apr	2.99**	0.16	0.94	0.00	0.72	0.04	0.67	0.77	0.91	0.07	0.43	0.31
May	2.27**	0.88	0.22	0.72	0.00	0.76	0.05	0.05	1.63	0.65	1.15	0.41
Jun	3.03**	0.12	0.98	0.04	0.76	0.00	0.71	0.81	0.87	0.11	0.39	0.35
Jul	2.32**	0.83	0.28	0.67	0.05	0.71	0.00	0.11	1.58	0.60	1.10	0.35
Aug	2.21**	0.93	0.17	0.77	0.05	0.81	0.11	0.00	1.69	0.71	1.20	0.46
Sep	3.90**	0.75	1.85	0.91	1.63	0.87	1.58	1.69	0.00	0.98	0.49	1.23
Oct	2.92**	0.23	0.87	0.07	0.65	0.11	0.60	0.71	0.98	0.00	0.49	0.25
Nov	3.41**	0.27	1.37	0.43	1.15	0.39	1.10	1.20	0.49	0.49	0.00	0.74
Dec	2.67**	0.47	0.63	0.31	0.41	0.35	0.35	0.46	1.23	0.25	0.74	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

An increase in the investor sentiment measure (ST) in December – highest for the year – in tandem with a decline in the residual return (AR) of the NSE portfolios in the same month suggest STs should be interpreted in absolute terms. Thus, an increase in investor sentiment could mean intense sell-off of losers by investors to meet varied year-end needs (as was the case in December) or preponderant buying of losers due to optimism associated with the turn of the year (as was the case in the month of January). As the observed June effect (based on AR) is not reflected in the investor sentiment measure, this interpretation is potentially constrained. The alternative view could be that one such calendar effect not corroborated by investor sentiment could be interpreted as fleeting. If this later view is taken, the January effect is effectively the only credible calendar anomaly associated with the overreaction effect on the NSE.

4.3 Findings of tests for investor overreaction and seasonality on the JSE

Evidence of overreaction was not found on the JSE. There were no statistically significant return differences between the study's JSE loser and winner portfolios. As can be seen in Table 11 below, the probability levels of the Chi-Square (H) values are greater than the alpha level of 0.05. This is the case for both when the test is corrected and uncorrected for ties. Average holding period abnormal return (AHPAR) for the extreme loser portfolio, P5, came out at 1.92% and is not found to be statistically different from those of the corresponding extreme winner portfolio, P1 with AHPAR of 1.36%. Specifically, when both the extreme loser and winner portfolios (P5 and P1 respectively) are compared using the Dunn's multiple comparison test, the z-value (1.07) is below the 1.96 threshold z-value for statistical significance at the 95% confidence level. Thus, the study finds there is no overreaction effect on the JSE.

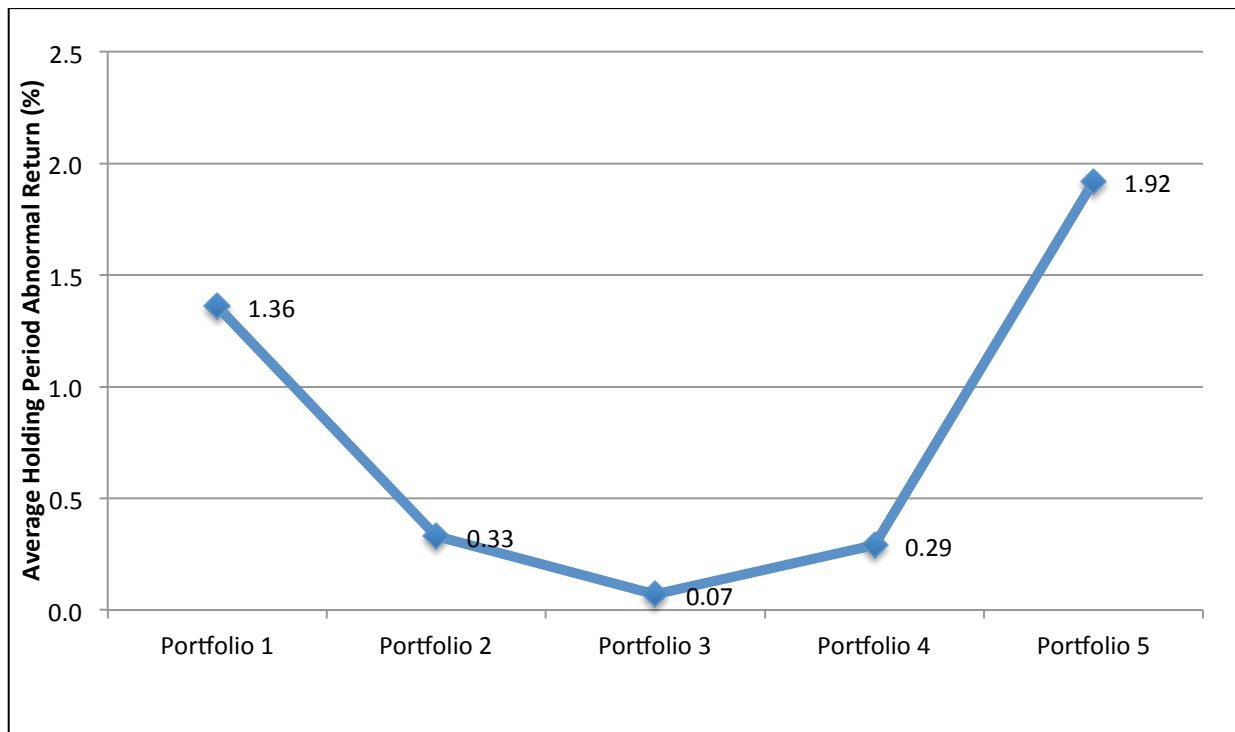


Figure 9: Means Plot of Average Holding Period Abnormal Returns (AHPARs) for JSE portfolios

Table 11: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for JSE Portfolios' Average Holding Period Abnormal Returns (AHPARs)

Method	DF	Chi-Square (H)	Prob Level	Decision (0.05)
Not Corrected for Ties	4	3.61	0.46	Accept H0
Corrected for Ties	4	3.61	0.46	Accept H0

Source: NCSS; Number Sets of Ties = 0, Multiplicity Factor = 0

Table 12: Kruskal-Wallis Multiple Comparison Test (Dunn's Test) Z-Values for JSE Portfolios' Average Holding Period Abnormal Returns (AHPARs)

AHPAR	1	2	3	4	5
1	0.00	1.05	1.61	1.67	1.07
2	1.05	0.00	0.56	0.63	0.02
3	1.61	0.56	0.00	0.06	0.54
4	1.67	0.63	0.06	0.00	0.61
5	1.07	0.02	0.54	0.61	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

In regard of investor sentiment (measured by AHPST) associated with securities that constitute the JSE quintile portfolios, the Kruskal Wallis One-Way ANOVA on Ranks test rejects the null hypothesis that the portfolios' AHPSTs have equal medians. However, apart from the second winner portfolio (P2), AHPST was largely the same for all the other four portfolios at circa 0.15%. Thus, although the Dunn's test finds that investor sentiment associated with most of the quintile portfolios are different from one another, there is not much difference between them in absolute terms. This supports the evidence of no overreaction effect on the JSE discussed earlier. Additionally, it suggests that when there is an overreaction effect on a bourse, there is likely to be a similar trend (albeit in absolute terms) observed with respect to investor sentiment. This was observed to be case in regard of the NSE. As the overreaction effect has been evidenced in past JSE studies, the relatively small portfolio AHPST differentials (though statistically significant) corroborate the lack of an overreaction effect in this study. The results imply the overreaction effect has been arbitrated away on the JSE.

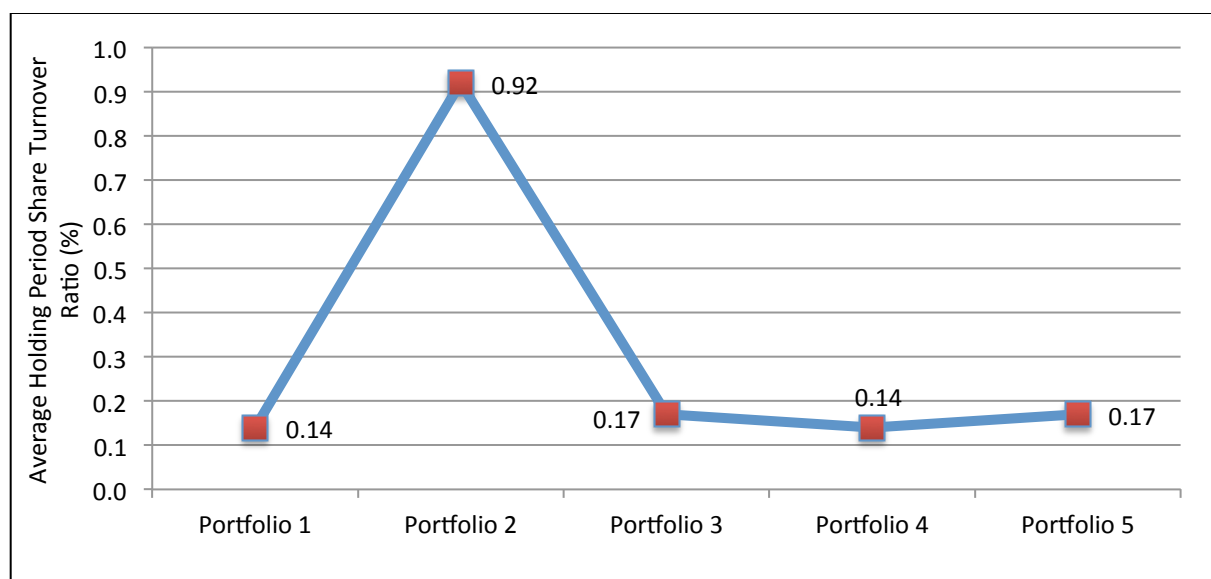


Figure 10: Means Plot of Average Holding Period Share Turnover Ratios (AHPSTs) for JSE Portfolios

Table 13: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for JSE Portfolios' AHPSTs

Method	DF	Chi-Square (H)	Prob Level	Decision (0.05)
Not Corrected for Ties	4	209.14	0	Reject H0
Corrected for Ties	4	209.14	0	Reject H0

Source: NCSS; Number Sets of Ties = 0, Multiplicity Factor = 0

Table 14: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for JSE Portfolios' AHPSTs

AHPST	1	2	3	4	5
1	0.00	10.10**	13.22**	10.32**	6.10**
2	10.10**	0.00	3.12**	0.22	4.00**
3	13.22**	3.12**	0.00	2.90**	7.12**
4	10.32**	0.22	2.90**	0.00	4.22**
5	6.10**	4.00**	7.12**	4.22**	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

However, some seasonality was still observed even in the absence of an overreaction effect on the JSE. As can be seen in the table below, the Chi-Square (H) value for both when the test is corrected for ties and otherwise is 90.80 with a probability level of zero, less than the 0.05 threshold probability level and thus allowing the rejection of the null hypothesis that all the median monthly residual returns are equal. January abnormal returns (ARs) are only statistically different from six other months. It is thus less convincing as an anomaly; especially in light of

the absence of an overreaction effect. This suggests the calendar anomaly is weak in the absence of an overreaction effect on the South African bourse. Alternatively, it means the January effect – irrespective of its association with other anomalies – has become weak on the JSE due to arbitrage.

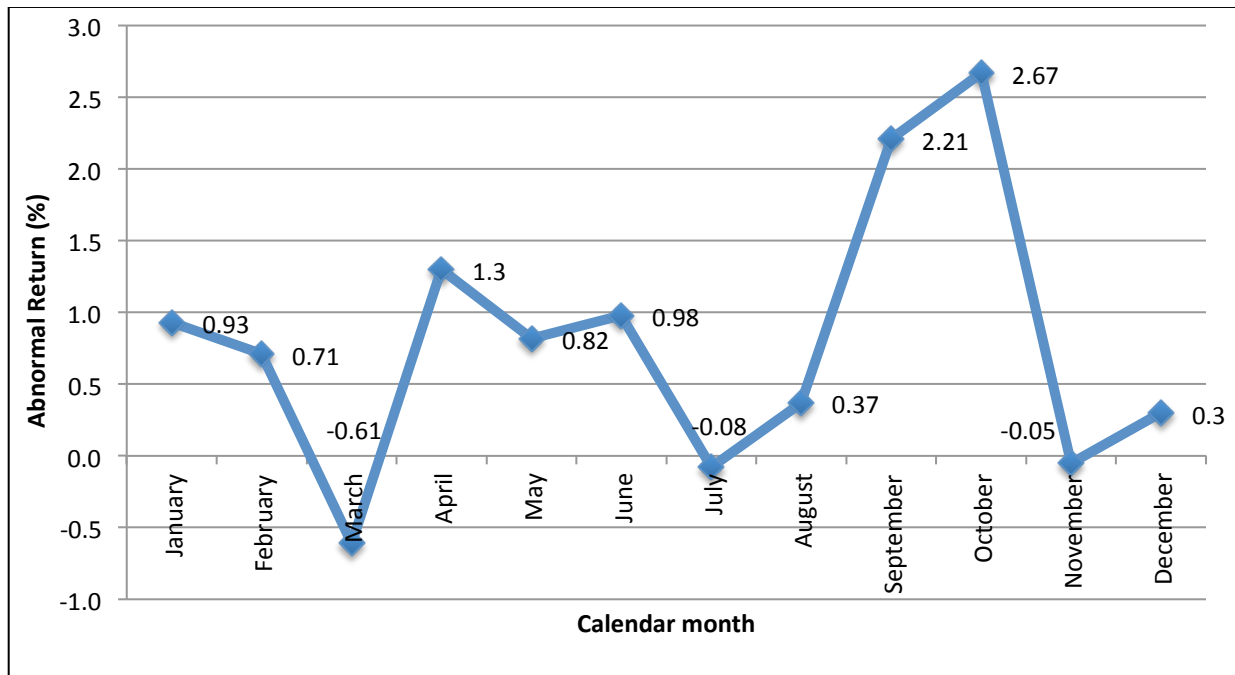


Figure 11: Means Plot of monthly abnormal returns (ARs) for JSE Portfolios

Table 15: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for JSE Portfolios' Monthly ARs

Method	DF	Chi-Square Prob (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	90.80	0.00	Reject H0
Corrected for Ties	11	90.80	0.00	Reject H0

Source: NCSS; Number Sets of Ties = 0, Multiplicity Factor = 0

The decline in AR in March (-0.6%) – the lowest of all the calendar months – is quite strong, however, as it is found to be statistically different from nine other months. This suggests a negative March effect on the JSE. Similarly, the Dunn's multiple comparison test shows October returns (AR of 2.7%) for JSE quintile portfolios are statistically higher than at least eight other months of the year, pointing to an October effect.

Table 16: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for JSE Portfolios' Monthly ARs

AHPAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.00	0.62	5.33**	0.72	0.64	0.25	2.90**	2.09*	1.14	4.74**	3.90**	2.48*
Feb	0.62	0.00	4.71**	0.11	0.03	0.37	2.29*	1.47	1.76	4.13**	3.28**	1.86
Mar	5.33**	4.71**	0.00	4.60**	4.68**	5.08**	2.42*	3.24**	6.47**	0.58	1.43	2.85**
Apr	0.72	0.11	4.60**	0.00	0.08	0.47	2.18*	1.37	1.86	4.02**	3.18**	1.76
May	0.64	0.03	4.68**	0.08	0.00	0.39	2.26*	1.45	1.78	4.10**	3.26**	1.84
Jun	0.25	0.37	5.08**	0.47	0.39	0.00	2.66**	1.84	1.39	4.50**	3.65**	2.23*
Jul	2.90**	2.29*	2.42*	2.18*	2.26*	2.66**	0.00	0.81	4.05**	1.84	1.00	0.42
Aug	2.09*	1.47	3.24**	1.37	1.45	1.84	0.81	0.00	3.23**	2.65**	1.81	0.39
Sep	1.14	1.76	6.47**	1.86	1.78	1.39	4.05**	3.23**	0.00	5.89**	5.04**	3.62**
Oct	4.74**	4.13**	0.58	4.02**	4.10**	4.50**	1.84	2.65**	5.89**	0.00	0.85	2.26*
Nov	3.90**	3.28**	1.43	3.18**	3.26**	3.65**	1.00	1.81	5.04**	0.85	0.00	1.42
Dec	2.48*	1.86	2.85**	1.76	1.84	2.23*	0.42	0.39	3.62**	2.26*	1.42	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

Judging from figure 12, it could be discerned that investor sentiment was particularly high in June on the JSE with ST of 0.41%. However, there is nothing to suggest that this presaged (or was in tandem) with heightened return activity, as the corresponding monthly AR (0.98%) was relatively lacklustre and not significantly different from the preceding month's AR of 0.82%. There is the possibility though that heightened investor sentiment is a leading indicator of return activity. This is because the relatively heightened JSE investor sentiment in June presaged a significant portfolio return decline in the subsequent month of July to -0.08% from 0.98% in the preceding month. This seems to be an isolated case, however, as a similar ST trend is not observed prior to the sharp return contraction in November to -0.05% from an October high of 2.67%.

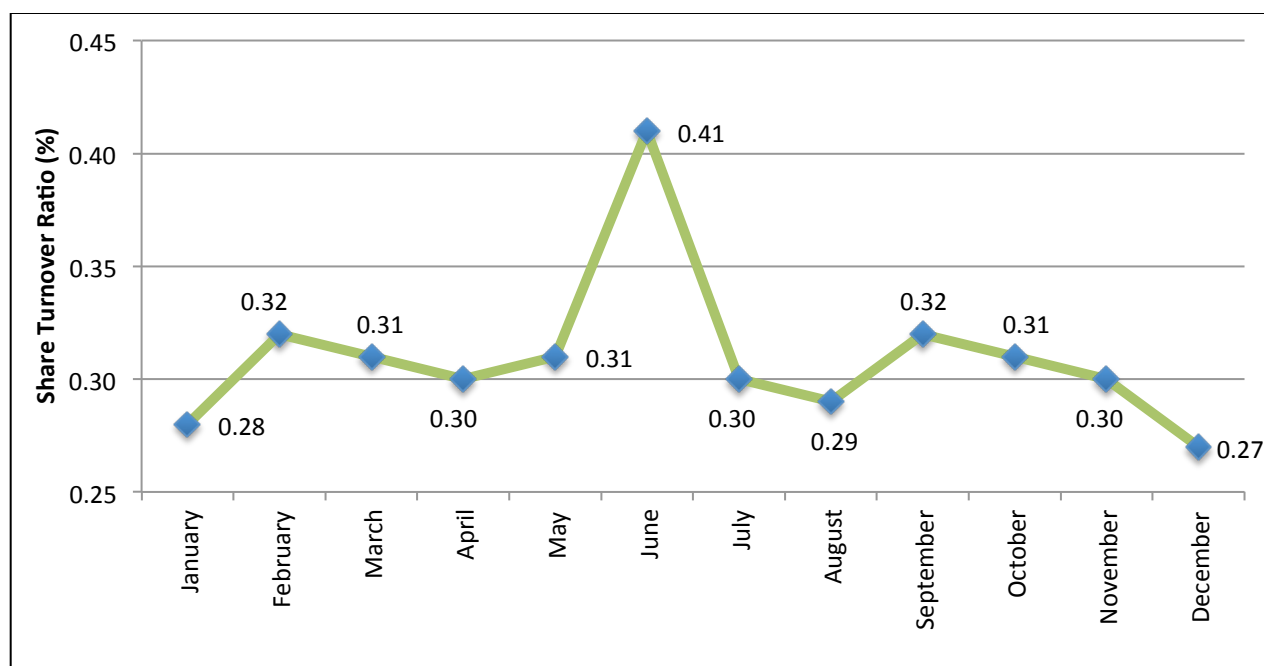


Figure 12: Means Plot of monthly share turnover ratios (STs) for JSE Portfolios

Table 17: Kruskal-Wallis One-Way ANOVA on Ranks Test Results for JSE Portfolios' Monthly STs

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	91.28	0	Reject H0
Corrected for Ties	11	91.28	0	Reject H0

Source: NCSS; Number Sets of Ties = 0, Multiplicity Factor = 0

Table 18: Kruskal-Wallis Multiple-Comparison Test (Dunn's Test) Z-Values for JSE Portfolios' Monthly STs

AHPAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.00	4.76**	5.24**	4.27**	4.91**	3.60**	1.65	2.34*	5.96**	3.36**	4.06**	0.44
Feb	4.76**	0.00	0.48	0.50	0.15	1.16	3.11**	2.42*	1.20	1.40	0.71	5.20**
Mar	5.24**	0.48	0.00	0.64	0.33	1.64	3.59**	2.90**	0.72	1.88	1.18	5.68**
Apr	4.27**	0.50	0.64	0.00	0.64	0.67	2.61*	1.92	1.70	0.91	0.21	4.70**
May	4.91**	0.15	0.33	0.64	0.00	1.31	3.26**	2.57*	1.05	1.55	0.85	5.35**
Jun	3.60**	1.16	1.64	0.67	1.31	0.00	1.94	1.26	2.36*	0.24	0.46	4.03**
Jul	1.65	3.11**	3.59**	2.61*	3.26**	1.94	0.00	0.69	4.31**	1.70	2.40*	2.09*
Aug	2.34*	2.42*	2.90**	1.92	2.57*	1.26	0.69	0.00	3.62**	1.02	1.71	2.78**
Sep	5.96**	1.20	0.72	1.70	1.05	2.36*	4.31**	3.62**	0.00	2.60**	1.91	6.40**
Oct	3.36**	1.40	1.88	0.91	1.55	0.24	1.70	1.02	2.60**	0.00	0.70	3.80**
Nov	4.06**	0.71	1.18	0.21	0.85	0.46	2.40*	1.71	1.91	0.70	0.00	4.49**
Dec	0.44	5.20**	5.68**	4.70**	5.35**	4.03**	2.09*	2.78**	6.40**	3.80**	4.49**	0.00

Source: NCSS; *Statistically significant if z-value > 1.96 at 95% confidence level;

**Statistically significant if z-value > 2.58 at 99% confidence level

5. SUMMARY AND CONCLUSION

5.1 Overview

The study finds evidence of overreaction and seasonality on the Nigerian Stock Exchange (NSE). These findings are in contrast to past studies of weak-form efficiency on the NSE (e.g., [Olowe, 1999](#); [Tijjani et al., 2009](#); [Okpara, 2010](#); et cetera). The observed overreaction effect on the NSE was accompanied by a January effect. Monthly seasonality was also found on the NSE in the calendar month of June – a “June Effect”; confirming earlier findings by [Claessens et al. \(1995\)](#) and [Alagidede \(2008\)](#). In regard of the supposed congruity of return and investor sentiment, only the NSE shows evidence of this. For the JSE, the study does not find evidence of overreaction.

Although, a mild January effect is evidenced, it is only marginally significant statistically. An “October effect” was found on the JSE, however. Prior studies (e.g., [Robins et al., 1999](#)) found a January effect and not an October effect on the JSE. The study’s findings imply the overreaction effect may have been arbitrated away over time as is the case for the JSE where overreaction was evidenced in the past (e.g., [Page and Way, 1992](#); [Robins et al., 1999](#); [Cubbin et al., 2006](#)). Thus, once market players become aware of an anomaly, it is less likely to become a source of consistent profit over time ([Schwert, 2002](#)). As this is the first documented overreaction effect on the NSE, it is likely to be arbitrated away in the Nigerian equity market over time as well. This would be an area for future research.

5.2 Summary of major findings relative to tested hypotheses

Hypothesis 1 (H_{01}): As markets are efficient, there is no investor overreaction effect on the NSE. Thus, Loser portfolios do not outperform winner portfolios on the NSE.

For the NSE, this is a pioneer overreaction study as a survey of the literature showed that hitherto there was yet to be an endeavor in this regard. Also, most of the prior efficiency studies for the bourse (e.g., [Olowe, 1999](#); [Tijjani et al., 2009](#); [Okpara, 2010](#)) were almost

unanimous in their findings of weak-form efficiency for the Nigerian stock exchange. As the NSE had characteristics similar to those in markets (e.g., Taiwan) where overreaction and the January effect had been evidenced (see [Lin and Swanson, 2010](#)), questions were raised about its supposed weak-form efficiency. This study finds the NSE is not weak-form efficient after all; as an overreaction effect is found on the bourse. The average holding period abnormal return (AHPAR) for the extreme loser portfolio, P5, is 7.08%, and that attributable to the extreme winner portfolio, P1, is 3.66%. And the difference is found to be statistically significant. This study thus rejects the null hypothesis that the NSE is efficient and asserts the bourse overreacts.

Hypothesis 2 (H_{o2}): As markets are efficient, there is no investor overreaction effect on the JSE. Thus, loser portfolios do not outperform winner portfolios on the JSE.

The overreaction effect had hitherto been evidenced on the JSE (e.g., [Page and Way, 1992](#); [Cubbin et al., 2006](#); [Hsieh and Hodnett, 2011](#)). The goal of this study was to investigate whether the anomaly still persists on the bourse. It does not, based on the study's findings. There were no statistically significant AHPAR differences between the study's JSE extreme loser and winner portfolios (P5 and P1), based on the Dunn's test. Thus, the null hypothesis that there is no investor overreaction effect on the JSE cannot be rejected. There is no longer an overreaction effect on the JSE.

Hypothesis 3 (H_{o3}): As markets are efficient, there is no January effect or other seasonality on the NSE. Thus, portfolio returns for the month of January (or any other calendar month) are not different from those of other calendar months on the NSE.

The study finds evidence of a January effect on the Nigerian Stock Exchange, an observation that is consistent with similar associations of seasonality with the overreaction effect evidenced in other markets. A "June" effect was also found, consistent with findings of earlier NSE studies (e.g., [Claessens et al., 1995](#); [Alagidede, 2008](#)); albeit not related to the overreaction effect. Abnormal Returns (ARs) for the calendar months of January and June were each statistically different from those of nine other months, based on the Dunn's test.

Hypothesis 4 (H_{04}): As markets are efficient, there is no January effect or other seasonality on the JSE. Thus, portfolio returns for the month of January (or any other calendar month) are not different from those of other calendar months on the JSE.

January returns were found to be statistically different from those of six other months including December. Although this could be interpreted as a mild January effect, it is not considered strong enough to warrant generalization. October returns – which were the highest with AR of 2.7% – were found to be statistically different from those of eight other months, however. Thus, there is an “October effect” on the Johannesburg Stock Exchange. The weak (or weakening) January effect on the JSE in the absence of an overreaction effect gives credence to studies that show an association between the two anomalies. This is especially as a strong January effect happens in tandem with the overreaction effect observed on the Nigerian bourse in this study.

Hypothesis 5 (H_{05}): As markets are efficient and investor sentiment behaves similarly as return, investor sentiment is the same irrespective of portfolio or calendar month.

This study finds investor sentiment varies per month and portfolio on both the NSE and JSE. On the NSE, investor sentiment (ST) is differential only in the calendar month of January. Also, the study finds January and December investor sentiments differ significantly on the NSE. In regard of congruity of return and investor sentiment, the study finds evidence of this on the NSE but not on the JSE. ARs for NSE portfolios moved in sync with the corresponding STs for all the months in the year except June and December. When NSE portfolios' AR increases to 20.6% in February from 5.5% in January, the corresponding investor sentiment measure almost doubles to 0.06% from 0.04% in the preceding month. A divergent pattern is observed for the observed June effect however. An increase in NSE portfolios' monthly AR to 13.8% in June from -2.8% in May happens in tandem with ST declining to 0.033% from 0.036% previously. Similarly, although ST was highest in December for the NSE quintile portfolios, AR declined in December to 0.2% from 5.2% in the preceding month. Thus, to determine the direction of investor sentiment, the corresponding return measure must be countenanced.

5.3 Contribution

5.3.1 Theoretical contribution

“Stock returns and trading volume are jointly determined by the same market dynamics and are inextricably linked in theory” (Lee and Swaminathan, 2000:2017). As the EMH asserts it shouldn’t be possible to consistently earn positive *ex post* abnormal returns using portfolios constituted based on *ex ante* returns, investor sentiment should similarly reflect this. Thus in an efficient market, *ex post* investor sentiment around the securities that constitute such portfolios should not be statistically different from their *ex ante* investor sentiment. This study finds that when portfolios are constituted in such a manner – in this instance based on the overreaction effect – investor sentiment does vary and with statistical significance if an overreaction effect is evidenced.

This study sought to increase our understanding of the relationship between the January effect and mean reversion of loser-winner portfolio returns and perhaps offer an alternative explanation. It conjectured that investor sentiment behaved in tandem with return and that optimism around the New Year could perhaps be responsible for the January effect. When investor overreaction was evidenced (like on the NSE), AHPAR and AHPST did trend together, particularly around the turn of the year. Both variables were statistically different for the extreme loser and winner portfolios (P5 and P1) and their January values were statistically different from at least eight other calendar months. When their outcomes are considered together, they point to a positive change in the mood of investors around the turn of the year.

One of the arguments proffered for the January effect conjectures year-end tax accounting and a desire by investors to earn tax credits are responsible for the anomaly. In this respect, both the NSE and JSE offered the opportunity to investigate if that were the case as there wasn’t a December tax year-end requirement in South Africa and Nigeria for the period of the dataset. A January effect is found to happen in tandem with overreaction on the NSE. Similarly, a weak (or diminishing) January effect is found on the JSE (even in the absence of overreaction). Clearly

the tax loss selling explanation for the January seasonal is not robust. Since if the January effect has been observed in markets where there is a December tax year-end and yet in this study – using JSE and NSE data to control for the tax explanation – the January seasonal is found, the argument could be made then that the anomaly is not peculiar to markets where there is a December tax year-end. As a stronger January effect has been observed on the JSE in the past (e.g., [Page and Way, 1992](#); [Robins et al., 1999](#)) – often in tandem with similarly oriented anomalies like the overreaction effect, size effect, etc. – a plausible argument that could be made is that the January effect has begun to be arbitrated away on the JSE.

5.3.2 Empirical contribution

This is the first overreaction study of the Nigerian Stock Exchange. Prior evidence ([Olowe, 1999](#); [Tijjani et al., 2009](#); [Okpara, 2010](#); et cetera) suggested it was weak-form efficient. However, there was a dearth of studies that used trading-rule based methodologies to investigate the efficiency of the bourse. Other drawbacks in these prior studies included small sample sizes: [Olowe \(1999\)](#) used fifty-nine (59) randomly selected securities and [Tijjani et al. \(2009\)](#) used sixty-nine (69). This study uses seventy-eight (78). Additionally, they didn't include observations beyond the year 2005-06, a period for which the Nigerian bourse experienced marked activity. Also, studies of other price-limit regulated equity markets (e.g., Taiwan) showed contrarian strategies earned superior returns, evidence in support of overreaction and converse to the efficient market argument ([Lin and Swanson, 2010](#)).

The intuition of this study, therefore, was that the Nigerian equity market wasn't likely to be efficient as suggested by the existing Nigerian efficiency literature. The findings of this study vindicate this intuition as Overreaction and January effects are evidenced on the NSE. The empirical contribution emanates from the pioneering status of this overreaction study for the Nigerian Stock Exchange. This is the first study that finds both overreaction and January effects in tandem on the NSE.

5.4 Implications for Practice

The investment profession continually seeks ways to beat the market to earn higher returns on the assets it manages. As the overreaction and the seasonal anomalies are amongst the few observed return dependencies that have endured, it enjoys keen interest in practice. Also, there is now significant interest in emerging markets like Nigeria and South Africa. However, global portfolio managers face informational challenges in these markets as there is a dearth of anomaly studies on the scale available in more developed markets. Thus, emerging-market focused fund managers should find the findings of this study useful.

Would investors be able to consistently earn superior returns using an investment strategy that leverages on the overreaction and seasonal anomalies? As the findings show, the anomalies dissipate over time (like was the case on the JSE). It remains to be seen how long both anomalies would endure on the NSE. That said, the study finds – up until 2011 – alpha returns could be consistently earned based on the overreaction and January effects in the Nigerian equity market.

The consistency in the finding of a June effect on the Nigerian Stock Exchange across two previous studies (Claessens et al., 1995; Alagidede, 2008) and now this one, suggests investors could build loser/winner portfolios to profit from the June seasonal on the Nigerian bourse as well. Can investors profit similarly from the observed “October Effect” on the JSE? Especially as this is a month characterized by declines in international stock markets owing to its notoriety as the month in which the great stock market crashes of 1929 and 1987 occurred. For practitioners, this should be worth exploring. This is because the South African financial markets are significantly linked with global markets.

5.5 Future research

The study shows share turnover ratio does qualify as a proxy for investor sentiment as – judging from the study’s findings – it indicates the intensity of views about securities that constitute

loser-winner portfolios. It does not however indicate by itself the direction of return performance. That is, when portfolios have a high investor sentiment measure, it could imply positive or negative abnormal returns. To determine the direction, a juxtaposition of the sentiment measure with return is necessary. This is in line with Lee and Swaminathan (2000) that suggest stock returns and trading volume are jointly determined by the same market dynamics. It would thus be interesting to know if this is also the case with other market anomalies. There would also be a need to test for persistence of the overreaction and January effects on the NSE in the future when more significant time-series on the market become available.

APPENDIX

Appendix 1 Sample of Nigerian Stock Exchange – Listed Securities

	Ticker	Description
1	7UP	7-Up Bottling Company Plc
2	ACADEMY	Academy Press
3	ACCESS	Access Bank Nigeria Plc
4	AGLEVENT	A. G. Leventis Nigeria
5	AIICO	Aiico Insurance
6	ALUMACO	Aluminium Manufacturer Of Nigeria
7	ASHAKACEM	Ashaka Cement
8	AVONCROWN	Avon Crowncaps And Containers
9	BERGER	Berger Paints
10	BETAGLAS	Beta Glass Company Plc
11	BOCGAS	Boc Gases Nigeria
12	CADBURY	Cadbury Nigeria Plc
13	CAP	Chemical And Allied Products Ltd
14	CCNN	Cement Company Of Northern Nigeria
15	CHAMPION	Champion Breweries
16	CHELLARAM	Chellarams
17	CHEVRON	Chevron Oil Nigeria Plc
18	CILEASING	C&I Leasing
19	CORNERST	Cornerstone Insurance
20	COSTAIN	Costain West Africa Plc
21	CRUSADER	Crusader Insurance
22	CUTIX	CUTIX
23	DNMEYER	D. N. Meyer
24	EKOCORP	Ekocorp
25	ENAMELWA	Nigerian Enamelware Plc
26	EVANSMED	Evans Medical

27	FIRSTALUM	First Aluminium Nigeria
28	FIRSTBANK	First Bank Nigeria
29	FLOURMILL	Flour Mills Of Nigeria Plc
30	FO	Forte Oil Plc
31	GLAXOSMITH	Glaxo Smithkline Beecham Nigeria
32	GUARANTY	Guaranty Trust Bank
33	GUINNESS	Guinness Nigeria Plc
34	JBERGER	Julius Berger (Nigeria) Plc
35	JOHNHOLT	John Holt
36	LASACO	Lasaco Assurance
37	LAWUNION	Law Union And Rock Insurance
38	LIVESTOCK	Livestocks Feeds
39	LONGMAN	Longman Nigeria
40	MAYBAKER	May And Baker Nigeria
41	MOBIL	Mobil Oil Nigeria
42	MORISON	Morison Industries
43	NB	Nigerian Breweries
44	NBC	Nigerian Bottling Company
45	NCR	Ncr (Nigeria)
46	NEIMETH	Neimeth International Pharmaceuticals Plc
47	NEM	Nem Insurance Plc
48	NESTLE	Nestle Nigeria Plc
49	NIG-GERMAN	Nigerian German Chemicals
50	NIGERINS	Niger Insurance
51	NIGROPES	Nigerian Ropes
52	NIWICABLE	Nigerian Wire And Cable Plc
53	NNFM	Northern Nigeria Flour Mills
54	OKOMUOIL	Okomu Oil
55	PHARMDEKO	Pharma Deko
56	POLYPROD	Poly Products

57	PRESTIGE	Prestige Insurance
58	PZ	Pz Industries
59	ROYALEX	Royal Exchange Assurance
60	RTBRISCOE	Rt Briscoe
61	SCOA	Scoa Nigeria
62	THOMASWY	Thomas Wyatt Nigeria.
63	TOTAL	Total Nigeria
64	TRIPPLEG	Tripple Gee And Company.
65	UAC-PROP	Uacn Property Development
66	UACN	Uacn Plc
67	UBA	United Bank For Africa
68	UBN	Union Bank Of Nigeria Plc
69	UNIC	Unic Insurance
70	UNILEVER	Unilever Nigeria
71	UNTL	United Nigeria Textile Plc
72	UPL	University Press
73	UTC	Utc Nigeria
74	VITAFOAM	Vitafoam Nigeria.
75	VONO	Vono Products
76	WAPCO	Lafarge Wapco Nigeria Plc
77	WAPIC	Wapic Insurance
78	WEMABANK	Wema Bank

Source: Nigerian Stock Exchange

Appendix 2 Sample of Johannesburg Stock Exchange – Listed Securities

	Ticker	Description
1	ABL	African Bank Inv Ltd
2	ACL	Arcelormittal Sa Limited
3	ADH	Advtech Ltd
4	ADI	Adaptit Holdings Limited
5	ADR	Adcorp Holdings Limited
6	ADW	African Dawn Capital Ltd
7	AEG	Aveng Group Limited
8	AFE	Aeci Limited
9	AFEP	Aeci Limited 5,5% Pref
10	AFR	Afgri Limited
11	AFX	African Oxygen Limited
12	AGI	Ag Industries Limited
13	AGL	Anglo American Plc
14	AHL	Ah-Vest Limited
15	ALT	Allied Technologies Ltd
16	AMA	Amalgamated App Hldgs Lt
17	AME	African Media Ent Ltd
18	AMS	Anglo American Plat Ltd
19	ANA	Adrenna Property Grp Ltd
20	ANG	Anglogold Ashanti Ltd
21	AON	African & Over Ent Ltd -
22	AOO	African & Over Ent Ltd
23	AOVP	African & Over Ent Ltd P
24	APK	Astrapak Limited
25	APN	Aspen Pharmacare Hldgs L
26	ARD	Ardor Sa Ltd
27	ARI	African Rainbow Min Ltd
28	ARL	Astral Foods Ltd

29	ASR	Assore Ltd
30	ATN	Allied Electronics Corp
31	AWT	Awethu Breweries Ltd
32	BAT	Brait Se
33	BAU	Bauba Platinum Limited
34	BAW	Barloworld Ltd
35	BAWP	Barworld Ltd 6%Pref
36	BCF	Bowler Metcalf Ltd
37	BEG	Beige Holdings Limited
38	BEL	Bell Equipment Ltd
39	BIL	Bhp Billiton Plc
40	BNT	Bonatla Property Hldgs
41	BRN	Brimstone Inv Corp Ltd-N
42	BSR	Basil Read Holdings Ltd
43	CCL	Compu Clearing Outs Ltd
44	CDZ	Cadiz Hldgs Ltd
45	CKS	Crookes Brothers Ltd
46	CMH	Combined Motor Hldgs Ltd
47	CND	Conduit Capital Ltd
48	COM	Comair Limited
49	CRG	Cargo Carriers Ltd
50	CSO	Capital Shop Cent Grp Pl
51	DAW	Distr And Warehousing
52	DGC	Digicore Holdings Limite
53	EHS	Evrz Highveld Steel & V
54	FSR	Firststrand Ltd
55	GDO	Gold One Int Ltd
56	GND	Grindrod Ltd
57	HAR	Harmony Gm Co Ltd
58	HWN	Howden Africa Hldgs Ltd

59	HYP	Hyprop Inv Ltd
60	IDQ	Indequity Group Ltd
61	ILV	Illovo Sugar Ltd
62	IMP	Impala Platinum Hlgs Ltd
63	ING	Ingenuity Property Inv
64	INL	Investec Ltd
65	IPL	Imperial Holdings Ltd
66	ISA	Isa Holdings Limited
67	ITE	Italtile Ltd
68	JCD	Jci Ltd
69	KAP	Kap International Hldgs
70	KGM	Kagiso Media Ltd
71	LBH	Liberty Holdings Ltd
72	LBHP	Liberty Hldgs 11C Pref
73	LNF	London Fin Inv Group Plc
74	LON	Lonmin Plc
75	VLE	Value Group Ltd

Source: McGregorBFA Database

Appendix 3: NCSS Statistical Analyses Report

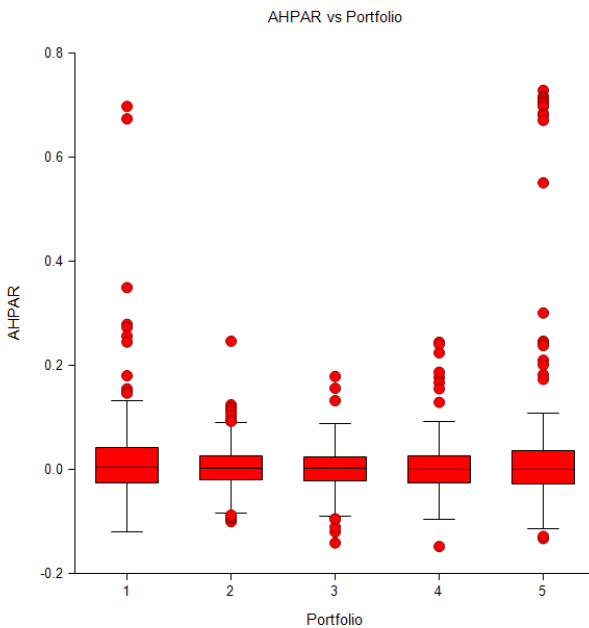
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	41.3161	0.000000	Reject
Kurtosis Normality of Residuals	27.7683	0.000000	Reject
Omnibus Normality of Residuals	2478.0999	0.000000	Reject
Modified-Levene Equal-Variance Test	16.9836	0.000000	Reject

Box Plot Section



Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	4	3.608245	0.461611	Accept H0
Corrected for Ties	4	3.608245	0.461611	Accept H0
Number Sets of Ties	0			
Multiplicity Factor	0			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
1	456	541551.00	1187.61	1.7086	0.003498048
2	456	520714.00	1141.92	0.0514	0.001961767
3	456	509499.00	1117.32	-0.8406	0.002495189
4	456	508262.00	1114.61	-0.9389	0.0006113497
5	456	520314.00	1141.04	0.0196	0.0007484739

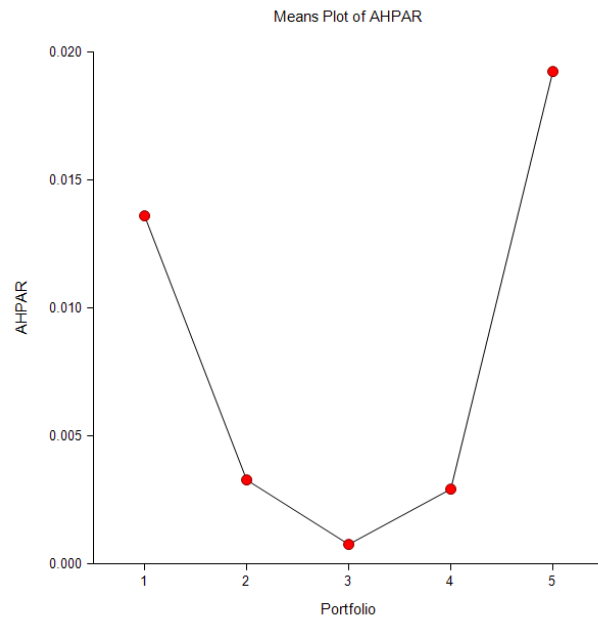
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.007958461		0.007958461
A: Portfolio				
1	456	0.01361404	0.003264964	0.005655584
2	456	0.003294444	0.003264964	-0.004664016
3	456	0.0007429685	0.003264964	-0.007215492
4	456	0.002907946	0.003264964	-0.005050514
5	456	0.0192329	0.003264964	0.01127444

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	1	2	3	4	5
1	0.0000	1.0481	1.6122	1.6744	1.0682
2	1.0481	0.0000	0.5641	0.6263	0.0201
3	1.6122	0.5641	0.0000	0.0622	0.5440
4	1.6744	0.6263	0.0622	0.0000	0.6062
5	1.0682	0.0201	0.5440	0.6062	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 2.8070

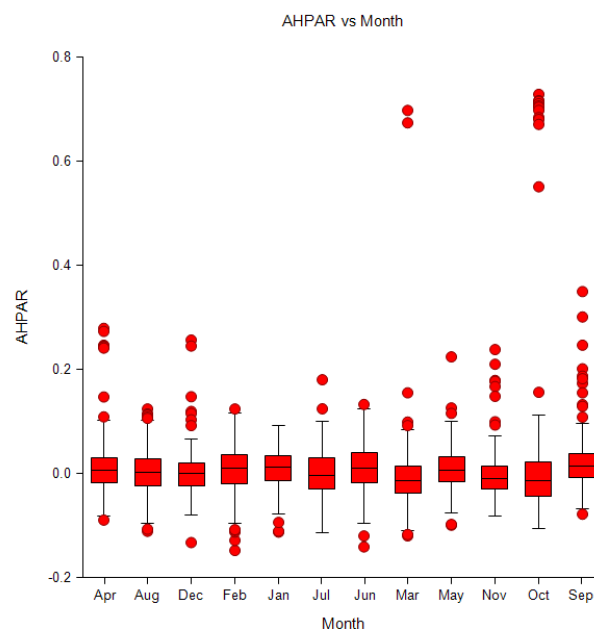
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	41.3116	0.000000	Reject
Kurtosis Normality of Residuals	27.7443	0.000000	Reject
Omnibus Normality of Residuals	2476.3926	0.000000	Reject
Modified-Levene Equal-Variance Test	7.8900	0.000000	Reject

Box Plot Section



Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	90.80025	0.000000	Reject H0
Corrected for Ties	11	90.80025	0.000000	Reject H0
Number Sets of Ties	0			
Multiplicity Factor	0			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
Apr	190	231523.00	1218.54	1.7067	0.006785138
Aug	190	213974.00	1126.18	-0.3132	0.001384753
Dec	190	208961.00	1099.79	-0.8902	0.0007620862
Feb	190	232871.00	1225.64	1.8619	0.009490015
Jan	190	240787.00	1267.30	2.7730	0.01113758
Jul	190	203528.00	1071.20	-1.5155	-0.004448066
Jun	190	237605.00	1250.55	2.4068	0.01081626
Mar	190	172430.00	907.53	-5.0949	-0.01439465
May	190	232543.00	1223.91	1.8241	0.006982313
Nov	190	190762.00	1004.01	-2.9849	-0.009306663
Oct	190	179915.00	946.92	-4.2334	-0.01412216
Sep	190	255441.00	1344.43	4.4597	0.01474684

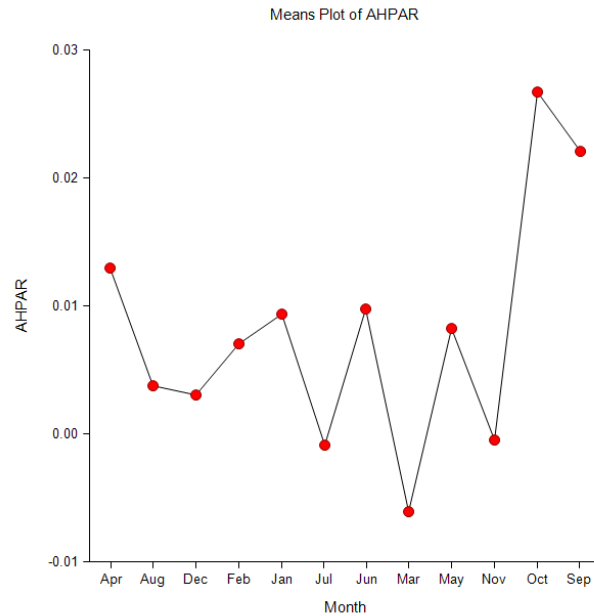
Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.007958461		0.007958461
A: Month				
Apr	190	0.01299782	0.005050557	0.005039361
Aug	190	0.003741745	0.005050557	-0.004216715
Dec	190	0.003031537	0.005050557	-0.004926923
Feb	190	0.007050655	0.005050557	-0.000907805
Jan	190	0.009331563	0.005050557	0.001373102
Jul	190	-0.0008428862	0.005050557	-0.008801347
Jun	190	0.009764351	0.005050557	0.00180589
Mar	190	-0.006101619	0.005050557	-0.01406008
May	190	0.008210718	0.005050557	0.0002522575
Nov	190	-0.0004798482	0.005050557	-0.008438309
Oct	190	0.02673484	0.005050557	0.01877638
Sep	190	0.02206264	0.005050557	0.01410418

Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Apr	Aug	Dec	Feb	Jan
Apr	0.0000	1.3675	1.7581	0.1050	0.7219
Aug	1.3675	0.0000	0.3906	1.4725	2.0894
Dec	1.7581	0.3906	0.0000	1.8632	2.4800
Feb	0.1050	1.4725	1.8632	0.0000	0.6168
Jan	0.7219	2.0894	2.4800	0.6168	0.0000
Jul	2.1815	0.8140	0.4234	2.2865	2.9034
Jun	0.4739	1.8414	2.2320	0.3689	0.2480
Mar	4.6047	3.2373	2.8466	4.7098	5.3266
May	0.0795	1.4470	1.8376	0.0256	0.6424
Nov	3.1762	1.8088	1.4181	3.2813	3.8981
Oct	4.0215	2.6540	2.2634	4.1265	4.7434
Sep	1.8638	3.2313	3.6219	1.7587	1.1419

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Jul	Jun	Mar	May	Nov
Apr	2.1815	0.4739	4.6047	0.0795	3.1762
Aug	0.8140	1.8414	3.2373	1.4470	1.8088
Dec	0.4234	2.2320	2.8466	1.8376	1.4181
Feb	2.2865	0.3689	4.7098	0.0256	3.2813
Jan	2.9034	0.2480	5.3266	0.6424	3.8981
Jul	0.0000	2.6554	2.4233	2.2610	0.9948
Jun	2.6554	0.0000	5.0787	0.3944	3.6502
Mar	2.4233	5.0787	0.0000	4.6842	1.4285
May	2.2610	0.3944	4.6842	0.0000	3.2557
Nov	0.9948	3.6502	1.4285	3.2557	0.0000
Oct	1.8400	4.4954	0.5833	4.1010	0.8452
Sep	4.0452	1.3898	6.4685	1.7843	5.0400

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Oct	Sep
Apr	4.0215	1.8638
Aug	2.6540	3.2313
Dec	2.2634	3.6219
Feb	4.1265	1.7587
Jan	4.7434	1.1419
Jul	1.8400	4.0452
Jun	4.4954	1.3898
Mar	0.5833	6.4685
May	4.1010	1.7843
Nov	0.8452	5.0400
Oct	0.0000	5.8853
Sep	5.8853	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

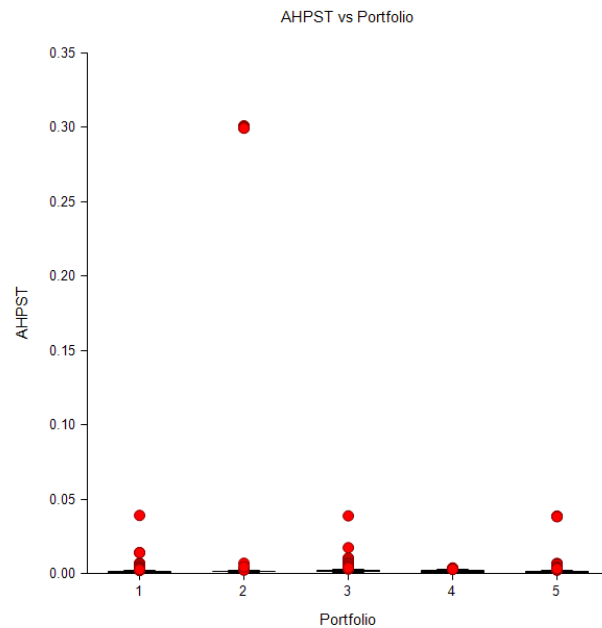
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	55.5383	0.000000	Reject
Kurtosis Normality of Residuals	31.8472	0.000000	Reject
Omnibus Normality of Residuals	4098.7461	0.000000	Reject
Modified-Levene Equal-Variance Test	11.2389	0.000000	Reject

Box Plot Section



Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	4	209.135	0.000000	Reject H0
Corrected for Ties	4	209.135	0.000000	Reject H0
Number Sets of Ties	0			
Multiplicity Factor	0			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
1	456	362098.00	794.07	-12.5634	0.001022544
2	456	562836.00	1234.29	3.4014	0.001324498
3	456	624839.00	1370.26	8.3325	0.001467351
4	456	567209.00	1243.88	3.7491	0.001341278
5	456	483358.00	1060.00	-2.9196	0.001176483

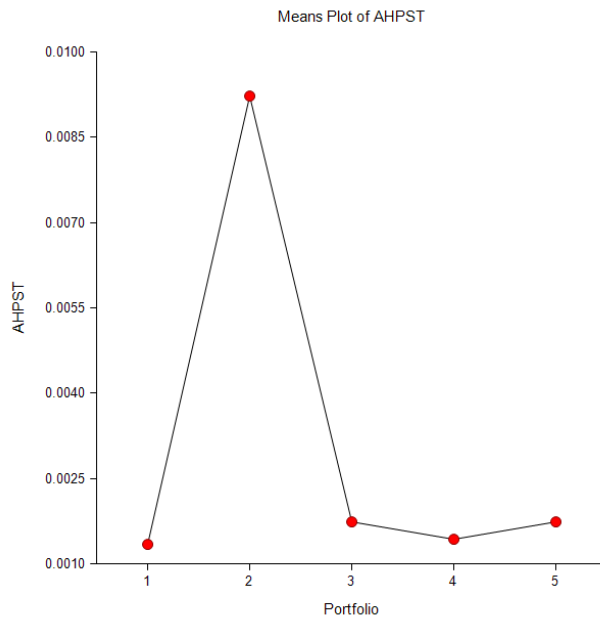
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.003098353		0.003098353
A: Portfolio				
1	456	0.001350745	0.001007872	-0.001747607
2	456	0.009226056	0.001007872	0.006127703
3	456	0.001746999	0.001007872	-0.001351354
4	456	0.001433704	0.001007872	-0.001664649
5	456	0.00173426	0.001007872	-0.001364092

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	1	2	3	4	5
1	0.0000	10.0970	13.2157	10.3170	6.0993
2	10.0970	0.0000	3.1187	0.2200	3.9977
3	13.2157	3.1187	0.0000	2.8988	7.1164
4	10.3170	0.2200	2.8988	0.0000	4.2177
5	6.0993	3.9977	7.1164	4.2177	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 2.8070

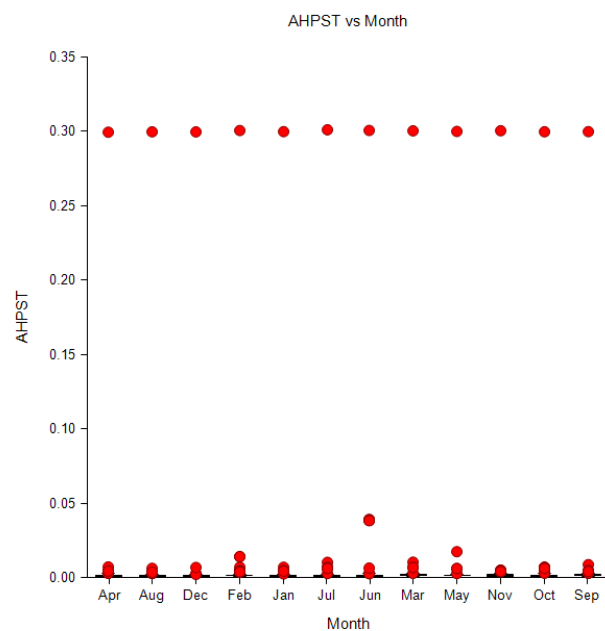
Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	56.0676	0.000000	Reject
Kurtosis Normality of Residuals	31.9606	0.000000	Reject
Omnibus Normality of Residuals	4165.0509	0.000000	Reject
Modified-Levene Equal-Variance Test	0.0408	0.999999	Accept

Box Plot Section



Analysis of Variance Report

Dataset C:\...\Desktop\jse_ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	91.27676	0.000000	Reject H0
Corrected for Ties	11	91.27676	0.000000	Reject H0
Number Sets of Ties	0			
Multiplicity Factor	0			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
Apr	190	228981.00	1205.16	1.4141	0.001284712
Aug	190	204297.00	1075.25	-1.4270	0.001216602
Dec	190	168628.00	887.52	-5.5325	0.001107575
Feb	190	235327.00	1238.56	2.1446	0.00133274
Jan	190	174230.00	917.00	-4.8878	0.001129161
Jul	190	195455.00	1028.71	-2.4447	0.001179333
Jun	190	220402.00	1160.01	0.4267	0.001270023
Mar	190	241464.00	1270.86	2.8509	0.001371596
May	190	237231.00	1248.58	2.3637	0.001403432
Nov	190	226267.00	1190.88	1.1017	0.001325912
Oct	190	217327.00	1143.83	0.0727	0.00126722
Sep	190	250731.00	1319.64	3.9176	0.001396766

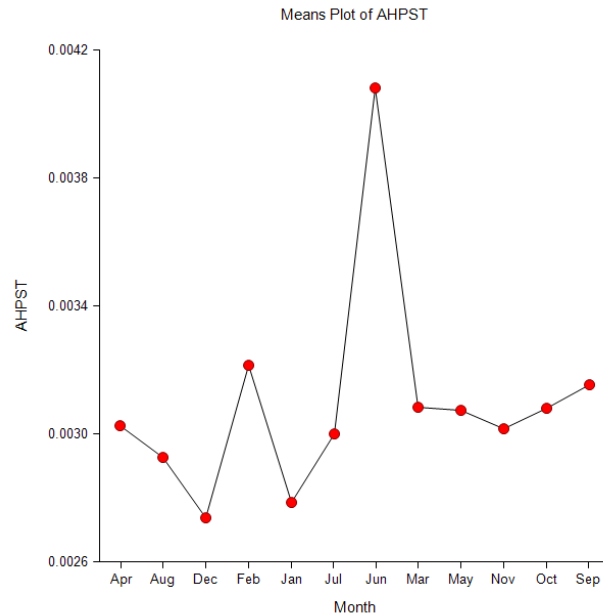
Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.003098353		0.003098353
A: Month				
Apr	190	0.003025805	0.001579462	-7.254779E-05
Aug	190	0.002925772	0.001579462	-0.0001725804
Dec	190	0.002737084	0.001579462	-0.0003612688
Feb	190	0.00321516	0.001579462	0.0001168069
Jan	190	0.002786606	0.001579462	-0.0003117471
Jul	190	0.003001225	0.001579462	-9.712781E-05
Jun	190	0.004081507	0.001579462	0.0009831543
Mar	190	0.003084078	0.001579462	-1.427481E-05
May	190	0.003074137	0.001579462	-2.421525E-05
Nov	190	0.003014877	0.001579462	-8.347572E-05
Oct	190	0.003080165	0.001579462	-1.818775E-05
Sep	190	0.003153817	0.001579462	5.546428E-05

Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Apr	Aug	Dec	Feb	Jan
Apr	0.0000	1.9235	4.7029	0.4945	4.2664
Aug	1.9235	0.0000	2.7795	2.4180	2.3429
Dec	4.7029	2.7795	0.0000	5.1974	0.4365
Feb	0.4945	2.4180	5.1974	0.0000	4.7609
Jan	4.2664	2.3429	0.4365	4.7609	0.0000
Jul	2.6125	0.6890	2.0905	3.1070	1.6539
Jun	0.6685	1.2550	4.0344	1.1630	3.5979
Mar	0.9727	2.8962	5.6756	0.4782	5.2391
May	0.6429	2.5663	5.3458	0.1484	4.9093
Nov	0.2115	1.7120	4.4914	0.7060	4.0549
Oct	0.9081	1.0153	3.7948	1.4026	3.3583
Sep	1.6948	3.6183	6.3978	1.2003	5.9612

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Analysis of Variance Report

Dataset C:\...\Desktop\jse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Jul	Jun	Mar	May	Nov
Apr	2.6125	0.6685	0.9727	0.6429	0.2115
Aug	0.6890	1.2550	2.8962	2.5663	1.7120
Dec	2.0905	4.0344	5.6756	5.3458	4.4914
Feb	3.1070	1.1630	0.4782	0.1484	0.7060
Jan	1.6539	3.5979	5.2391	4.9093	4.0549
Jul	0.0000	1.9440	3.5852	3.2553	2.4010
Jun	1.9440	0.0000	1.6412	1.3114	0.4570
Mar	3.5852	1.6412	0.0000	0.3299	1.1842
May	3.2553	1.3114	0.3299	0.0000	0.8544
Nov	2.4010	0.4570	1.1842	0.8544	0.0000
Oct	1.7043	0.2396	1.8808	1.5510	0.6966
Sep	4.3073	2.3633	0.7221	1.0520	1.9063

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Oct	Sep
Apr	0.9081	1.6948
Aug	1.0153	3.6183
Dec	3.7948	6.3978
Feb	1.4026	1.2003
Jan	3.3583	5.9612
Jul	1.7043	4.3073
Jun	0.2396	2.3633
Mar	1.8808	0.7221
May	1.5510	1.0520
Nov	0.6966	1.9063
Oct	0.0000	2.6030
Sep	2.6030	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

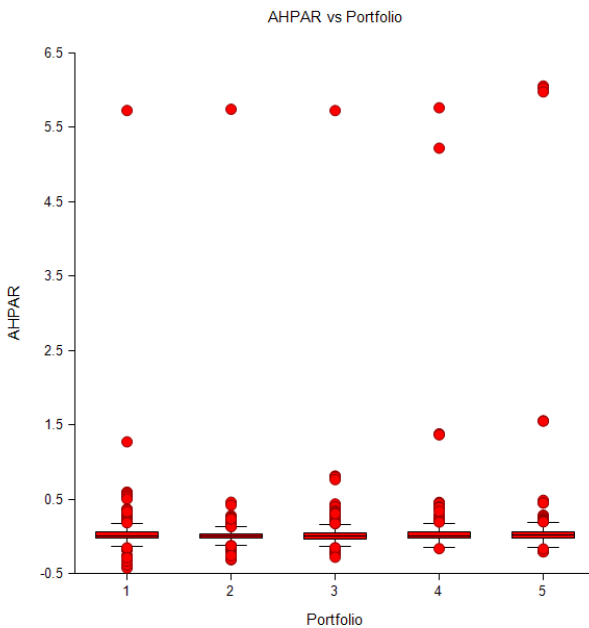
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
Response AHPAR

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	57.2269	0.000000	Reject
Kurtosis Normality of Residuals	32.5200	0.000000	Reject
Omnibus Normality of Residuals	4332.4689	0.000000	Reject
Modified-Levene Equal-Variance Test	0.7146	0.581906	Accept

Box Plot Section



Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	4	13.31977	0.009815	Reject H0
Corrected for Ties	4	13.31978	0.009815	Reject H0
Number Sets of Ties	180			
Multiplicity Factor	1080			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
1	456	519935.00	1140.21	-0.0106	0.007290974
2	456	490483.00	1075.62	-2.3529	-0.001712296
3	456	507514.00	1112.97	-0.9984	0.001531607
4	456	522416.00	1145.65	0.1867	0.005590129
5	456	559992.00	1228.05	3.1752	0.0169767

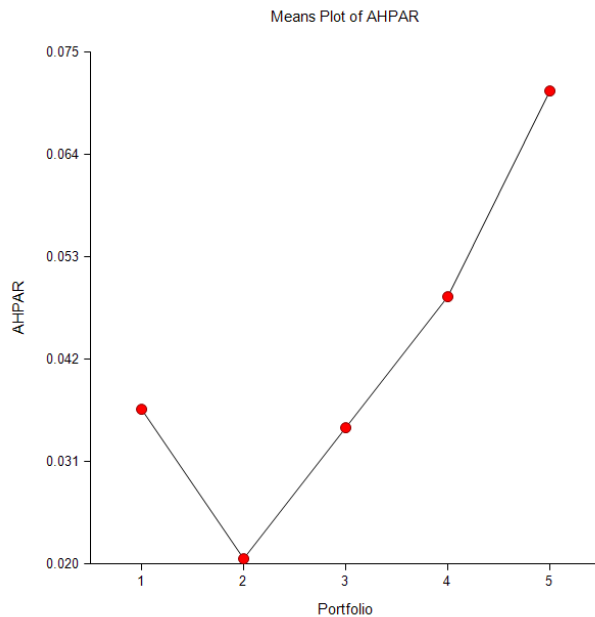
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_months_portfolio.NCSS
Response AHPAR

Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.0422451		0.0422451
A: Portfolio				
1	456	0.03658571	0.01683029	-0.005659393
2	456	0.0205865	0.01683029	-0.02165861
3	456	0.0345799	0.01683029	-0.007665202
4	456	0.04867619	0.01683029	0.00643109
5	456	0.07079721	0.01683029	0.02855211

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	1	2	3	4	5
1	0.0000	1.4814	0.6248	0.1248	2.0148
2	1.4814	0.0000	0.8566	1.6062	3.4963
3	0.6248	0.8566	0.0000	0.7496	2.6396
4	0.1248	1.6062	0.7496	0.0000	1.8901
5	2.0148	3.4963	2.6396	1.8901	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 2.8070

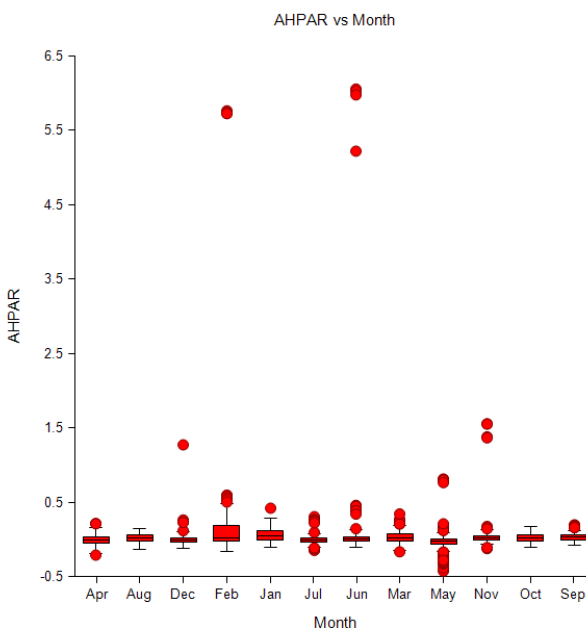
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_months_portfolio.NCSS
Response AHPAR

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	56.9244	0.000000	Reject
Kurtosis Normality of Residuals	32.4633	0.000000	Reject
Omnibus Normality of Residuals	4294.2562	0.000000	Reject
Modified-Levene Equal-Variance Test	5.6884	0.000000	Reject

Box Plot Section



Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_months_portfolio.NCSS
Response AHPAR

Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	241.0178	0.000000	Reject H0
Corrected for Ties	11	241.0179	0.000000	Reject H0
Number Sets of Ties	180			
Multiplicity Factor	1080			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
Apr	190	176391.00	928.37	-4.6390	-0.01508332
Aug	190	237142.00	1248.12	2.3535	0.02066036
Dec	190	175076.00	921.45	-4.7904	-0.01255408
Feb	190	259191.00	1364.16	4.8913	0.0177944
Jan	190	271837.00	1430.72	6.3469	0.04407622
Jul	190	162656.00	856.08	-6.2199	-0.01605322
Jun	190	212119.00	1116.42	-0.5267	0.0009530014
Mar	190	240693.00	1266.81	2.7622	0.02247539
May	190	142237.00	748.62	-8.5702	-0.02453966
Nov	190	242532.00	1276.48	2.9739	0.01518636
Oct	190	226295.00	1191.03	1.1050	0.01479874
Sep	190	254171.00	1337.74	4.3135	0.02633867

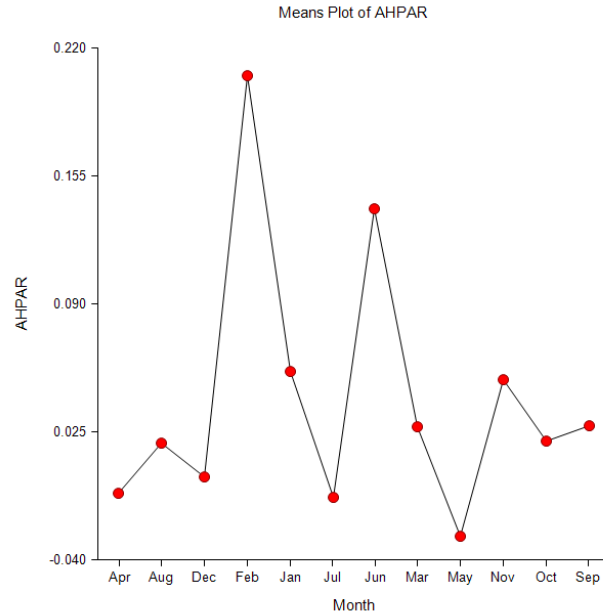
Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.0422451		0.0422451
A: Month				
Apr	190	-0.006052889	0.02572402	-0.04829799
Aug	190	0.01908218	0.02572402	-0.02316292
Dec	190	0.002267322	0.02572402	-0.03997778
Feb	190	0.2061734	0.02572402	0.1639283
Jan	190	0.05552144	0.02572402	0.01327633
Jul	190	-0.008299578	0.02572402	-0.05054468
Jun	190	0.1383079	0.02572402	0.09606276
Mar	190	0.02770652	0.02572402	-0.01453859
May	190	-0.02793368	0.02572402	-0.07017878
Nov	190	0.0515848	0.02572402	0.009339699
Oct	190	0.0202568	0.02572402	-0.0219883
Sep	190	0.02832705	0.02572402	-0.01391805

Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
 Response AHPAR

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Apr	Aug	Dec	Feb	Jan
Apr	0.0000	4.7339	0.1025	6.4521	7.4375
Aug	4.7339	0.0000	4.8364	1.7181	2.7036
Dec	0.1025	4.8364	0.0000	6.5545	7.5400
Feb	6.4521	1.7181	6.5545	0.0000	0.9854
Jan	7.4375	2.7036	7.5400	0.9854	0.0000
Jul	1.0703	5.8042	0.9678	7.5224	8.5078
Jun	2.7841	1.9499	2.8865	3.6680	4.6534
Mar	5.0106	0.2767	5.1131	1.4414	2.4269
May	2.6614	7.3953	2.5589	9.1135	10.0989
Nov	5.1539	0.4200	5.2564	1.2981	2.2835
Oct	3.8887	0.8452	3.9912	2.5634	3.5488
Sep	6.0609	1.3270	6.1634	0.3912	1.3766

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_months_portfolio.NCSS
Response AHPAR

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Jul	Jun	Mar	May	Nov
Apr	1.0703	2.7841	5.0106	2.6614	5.1539
Aug	5.8042	1.9499	0.2767	7.3953	0.4200
Dec	0.9678	2.8865	5.1131	2.5589	5.2564
Feb	7.5224	3.6680	1.4414	9.1135	1.2981
Jan	8.5078	4.6534	2.4269	10.0989	2.2835
Jul	0.0000	3.8543	6.0809	1.5911	6.2242
Jun	3.8543	0.0000	2.2266	5.4455	2.3699
Mar	6.0809	2.2266	0.0000	7.6720	0.1433
May	1.5911	5.4455	7.6720	0.0000	7.8153
Nov	6.2242	2.3699	0.1433	7.8153	0.0000
Oct	4.9590	1.1046	1.1219	6.5501	1.2652
Sep	7.1312	3.2768	1.0503	8.7223	0.9070

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPAR	Oct	Sep
Apr	3.8887	6.0609
Aug	0.8452	1.3270
Dec	3.9912	6.1634
Feb	2.5634	0.3912
Jan	3.5488	1.3766
Jul	4.9590	7.1312
Jun	1.1046	3.2768
Mar	1.1219	1.0503
May	6.5501	8.7223
Nov	1.2652	0.9070
Oct	0.0000	2.1722
Sep	2.1722	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

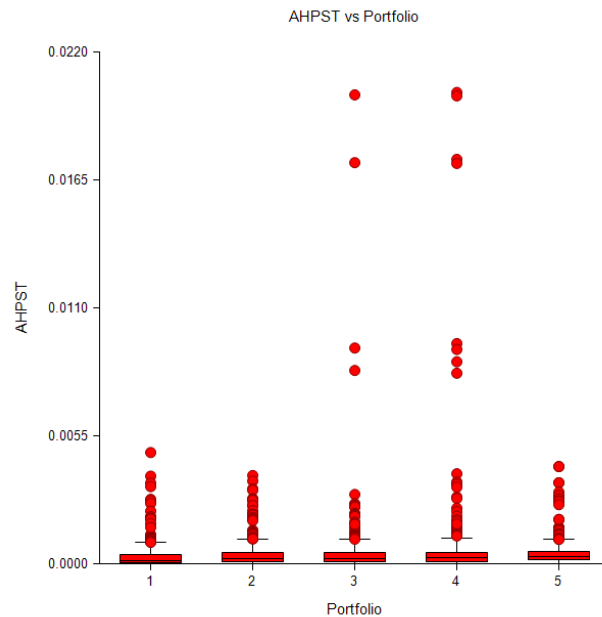
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	53.7434	0.000000	Reject
Kurtosis Normality of Residuals	31.8148	0.000000	Reject
Omnibus Normality of Residuals	3900.5371	0.000000	Reject
Modified-Levene Equal-Variance Test	4.1004	0.002584	Reject

Box Plot Section



Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	4	63.94954	0.000000	Reject H0
Corrected for Ties	4	63.94954	0.000000	Reject H0
Number Sets of Ties	240			
Multiplicity Factor	1440			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
1	456	437467.00	959.36	-6.5693	0.0001440386
2	456	513661.00	1126.45	-0.5096	0.0002293833
3	456	528079.00	1158.07	0.6371	0.0002313137
4	456	525712.00	1152.88	0.4489	0.0002498111
5	456	595421.00	1305.75	5.9929	0.0002992026

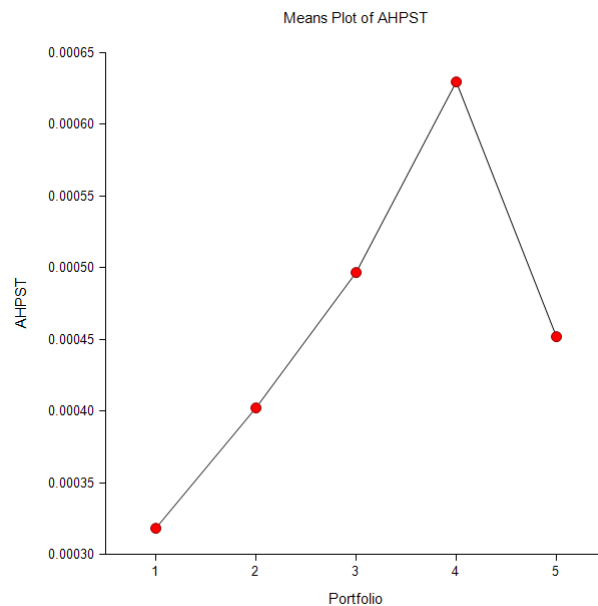
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.0004596893		0.0004596893
A: Portfolio				
1	456	0.0003183477	5.413653E-05	-0.0001413416
2	456	0.000402005	5.413653E-05	-5.768433E-05
3	456	0.0004967565	5.413653E-05	3.706713E-05
4	456	0.0006295532	5.413653E-05	0.0001698639
5	456	0.0004517843	5.413653E-05	-7.905063E-06

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	1	2	3	4	5
1	0.0000	3.8325	4.5577	4.4387	7.9450
2	3.8325	0.0000	0.7252	0.6062	4.1125
3	4.5577	0.7252	0.0000	0.1191	3.3873
4	4.4387	0.6062	0.1191	0.0000	3.5063
5	7.9450	4.1125	3.3873	3.5063	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 2.8070

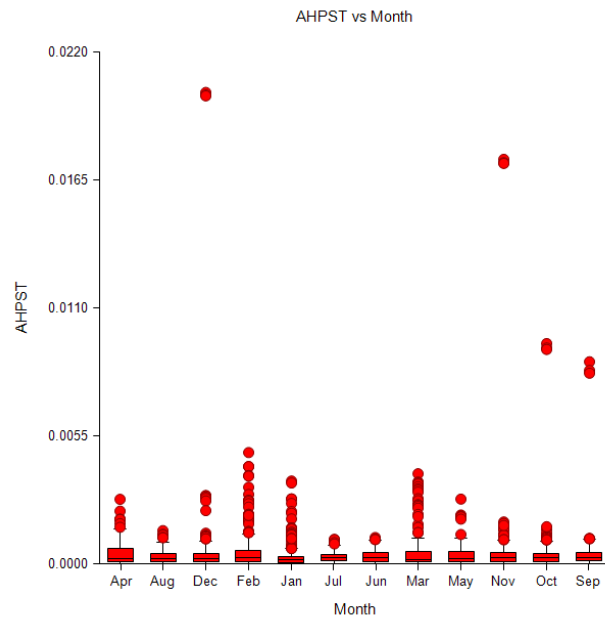
Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Tests of Assumptions Section

Assumption	Test Value	Prob Level	Decision (0.05)
Skewness Normality of Residuals	53.6734	0.000000	Reject
Kurtosis Normality of Residuals	31.7974	0.000000	Reject
Omnibus Normality of Residuals	3891.9042	0.000000	Reject
Modified-Levene Equal-Variance Test	2.7350	0.001616	Reject

Box Plot Section



Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpar_ahpst_months_portfolio.NCSS
Response AHPST

Kruskal-Wallis One-Way ANOVA on Ranks

Hypotheses

H0: All medians are equal.

Ha: At least two medians are different.

Test Results

Method	DF	Chi-Square (H)	Prob Level	Decision(0.05)
Not Corrected for Ties	11	20.97861	0.033593	Reject H0
Corrected for Ties	11	20.97861	0.033593	Reject H0
Number Sets of Ties	240			
Multiplicity Factor	1440			

Group Detail

Group	Count	Sum of Ranks	Mean Rank	Z-Value	Median
Apr	190	221963.00	1168.23	0.6064	0.000237925
Aug	190	212040.00	1116.00	-0.5358	0.0002310263
Dec	190	217949.00	1147.10	0.1443	0.0002337526
Feb	190	224006.00	1178.98	0.8415	0.0002523445
Jan	190	183629.00	966.47	-3.8059	0.000158072
Jul	190	213424.00	1123.28	-0.3765	0.0002422282
Jun	190	222485.00	1170.97	0.6664	0.0002811582
Mar	190	209886.00	1104.66	-0.7837	0.0001973242
May	190	212731.00	1119.64	-0.4563	0.0002168406
Nov	190	227440.00	1197.05	1.2368	0.0002765841
Oct	190	221109.00	1163.73	0.5081	0.0002526607
Sep	190	233678.00	1229.88	1.9548	0.000268019

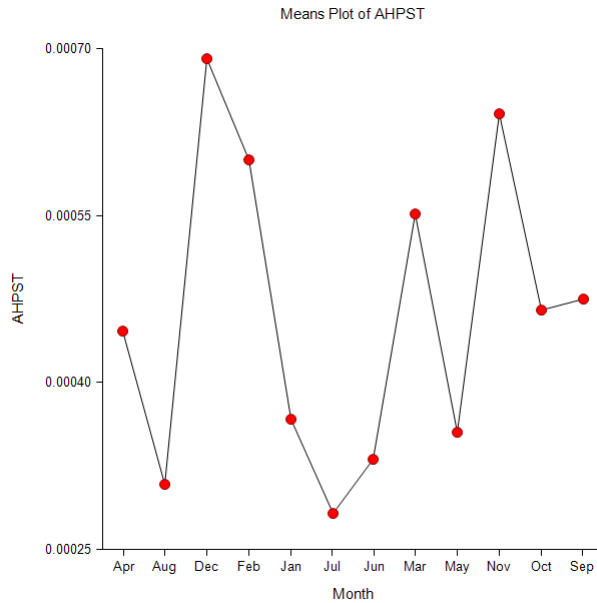
Means and Effects Section

Term	Count	Mean	Standard Error	Effect
All	2280	0.0004596893		0.0004596893
A: Month				
Apr	190	0.00044644	8.379477E-05	-1.324939E-05
Aug	190	0.0003088745	8.379477E-05	-0.0001508149
Dec	190	0.0006914234	8.379477E-05	0.000231734
Feb	190	0.0006003864	8.379477E-05	0.0001406971
Jan	190	0.0003666207	8.379477E-05	-9.306862E-05
Jul	190	0.0002821237	8.379477E-05	-0.0001775657
Jun	190	0.0003312363	8.379477E-05	-0.000128453
Mar	190	0.0005517898	8.379477E-05	9.210048E-05
May	190	0.0003556691	8.379477E-05	-0.0001040202
Nov	190	0.00064137	8.379477E-05	0.0001816807
Oct	190	0.0004650934	8.379477E-05	5.404058E-06
Sep	190	0.0004752449	8.379477E-05	1.555554E-05

Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_ahpst_months_portfolio.NCSS
 Response AHPST

Plots of Means Section



Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Apr	Aug	Dec	Feb	Jan
Apr	0.0000	0.7732	0.3128	0.1592	2.9871
Aug	0.7732	0.0000	0.4605	0.9324	2.2139
Dec	0.3128	0.4605	0.0000	0.4720	2.6743
Feb	0.1592	0.9324	0.4720	0.0000	3.1463
Jan	2.9871	2.2139	2.6743	3.1463	0.0000
Jul	0.6654	0.1078	0.3526	0.8246	2.3217
Jun	0.0407	0.8139	0.3535	0.1185	3.0278
Mar	0.9411	0.1678	0.6283	1.1003	2.0460
May	0.7194	0.0538	0.4066	0.8786	2.2677
Nov	0.4268	1.2000	0.7396	0.2676	3.4139
Oct	0.0665	0.7067	0.2462	0.2257	2.9206
Sep	0.9129	1.6861	1.2257	0.7537	3.9000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Analysis of Variance Report

Dataset C:\...\Desktop\nse ahpst_ahpst_months_portfolio.NCSS
Response AHPST

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Jul	Jun	Mar	May	Nov
Apr	0.6654	0.0407	0.9411	0.7194	0.4268
Aug	0.1078	0.8139	0.1678	0.0538	1.2000
Dec	0.3526	0.3535	0.6283	0.4066	0.7396
Feb	0.8246	0.1185	1.1003	0.8786	0.2676
Jan	2.3217	3.0278	2.0460	2.2677	3.4139
Jul	0.0000	0.7061	0.2757	0.0540	1.0922
Jun	0.7061	0.0000	0.9818	0.7601	0.3861
Mar	0.2757	0.9818	0.0000	0.2217	1.3679
May	0.0540	0.7601	0.2217	0.0000	1.1462
Nov	1.0922	0.3861	1.3679	1.1462	0.0000
Oct	0.5988	0.1072	0.8745	0.6528	0.4933
Sep	1.5783	0.8722	1.8540	1.6323	0.4861

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

Kruskal-Wallis Multiple-Comparison Z-Value Test (Dunn's Test)

AHPST	Oct	Sep
Apr	0.0665	0.9129
Aug	0.7067	1.6861
Dec	0.2462	1.2257
Feb	0.2257	0.7537
Jan	2.9206	3.9000
Jul	0.5988	1.5783
Jun	0.1072	0.8722
Mar	0.8745	1.8540
May	0.6528	1.6323
Nov	0.4933	0.4861
Oct	0.0000	0.9794
Sep	0.9794	0.0000

Regular Test: Medians significantly different if z-value > 1.9600

Bonferroni Test: Medians significantly different if z-value > 3.3678

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