AN EMPIRICAL STUDY OF PRICE CLUSTERING ON THE NAIROBI SECURITIES EXCHANGE

BY

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A RESEARCH PROJECT REPORT SUBMITTED TO THE SCHOOL OF BUSINESS IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF BUSINESS ADMINISTRATION DEGREE OF THE UNIVERSITY OF NAIROBI

NOVEMBER 2014

DECLARATION

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This research report is my original work and has not been presented for award of any degree in any other university.

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DEDICATION

I dedicate this research project to my late mother Felicitas Namaemba Lugongo and my father Samuel Lugongo. You were very supportive to me throughout my entire education, and I forever remain indebted to you.

ACKNOWLEDGEMENT

I would like to extend appreciation to my supervisor, family, friends and the Nairobi Securities Exchange for their unwavering support towards the completion of my project. Special thanks to Dr. Sifunjo Kisaka, my father Samuel Lugongo and Godfrey Omilly who is the Senior Product Development Officer at the NSE.

I do also thank the Lord for the strength, good health, and sound mind throughout the period of my MBA study.

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LIST OF ABBREVIATIONS AND ACRONYMS

ADR	American Depository Receipts
AMEX	American Stock Exchange
ASX	Australian Stock Exchange
CDS	Central Depository System
CMA	Capital Markets Authority
NASDAQ	National Association of Securities Dealers Automated Quotations
SES	Stock Exchange of Singapore
NSE	Nairobi Securities Exchange
NYSE	New York Stock Exchange
SEAQS	Stock Exchange Quotation System
SEATS	Stock Exchange Automated Trading System
TSE	Tokyo Stock Exchange

ABSTRACT

Price clustering is a phenomenon where some prices are observed more frequently than others. Several hypotheses have been put forth to explain this phenomenon. This study therefore set to empirically investigate price clustering phenomenon on the Nairobi Securities Exchange for the period 2009 to 2013. The study used secondary sources of data obtained from the Nairobi Securities Exchange and revealed that there is a preference by investors for stock whose prices end with the digit 5 which accounted for 67.88 percent of all the stocks examined. This was followed by stocks whose prices ended with the digit 0 which accounted for 4.55 percent. In order to establish the determinants of this observed behaviour, a multivariate regression model was adopted where price clustering was regressed against stock volatility, number of trades, market capitalization, and own stock price. The regression results indicated that the number of trades and market capitalization were positive and significantly related to price clustering. Stock price was found to be negative and significantly related to price clustering. On the other hand, stock volatility was established to be an insignificant predictor of price clustering. The multivariate regression model was found to be significant in explaining the observed relationship and that 15.4 percent of the variance in price clustering was explained by the number of trades, stock volatility, own stock price and the market capitalization.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

1.1.1 Price Clustering

Price clustering is the phenomenon in which the last digit of a price tends to occur at specific numbers. Basically in efficient markets, the last digits should exhibit a uniform distribution and clustering of price should not be expected to exist. However, this is hardly the case as researchers have time and again documented evidence of clustering in financial markets.

Osborne (1962), Harris (1991) and Christie, Harris, & Schultz (1994) document that prices cluster around whole numbers and common fractions. This phenomenon occurs for both stock quotes and transaction prices, and is persistent through time and across different stocks and stock markets. Ball, Torus, & Tschoegl, (1985) finds a similar clustering in the London gold market, as do Goodhart & Curcio (1991) in foreign exchange rates. Similar studies also show that residential real estate prices tend to cluster on certain multiples of a currency unit as is also the case with the derivatives market (Schwartz, Van Ness, & Ness, 2004) and bank deposit rates (Kahn, Pennachi, & Sopranzetti, 1999).

Clustering is a numbers anomaly associated with investors' irrational behaviour. Harris (1991) asserts that price clustering occurs because traders use a discrete set of prices to specify their terms of trades and lower the costs of negotiating. Negotiations may therefore converge more rapidly since playful offers and counteroffers are restricted. A small price set also limits the amount of information that must be exchanged between negotiating traders which effectively reduces the time to strike a bargain.

Exchange regulations account for why decimal places more than two (or fractions smaller than eighths) are rarely used. Many exchanges require that quotes and transaction prices are stated as some multiple of a minimum price variation, or trading tick. These regulations may simply ensure that all traders use the same discrete price set so that the benefits of discrete prices can be realized. Alternatively, exchanges may regulate minimum price variations to affect the provision of liquidity in their markets. The minimum price variation determines both the minimum quotable bid/ask spread and the maximum value of time precedence at a given price. The Nairobi Securities Exchange for instance allows bidding advances and dealing spreads to be quoted in bundles of 5 cents or more. Integer clustering or clustering on larger fractions can be explained if traders choose to restrict further their terms of trade to coarser (few) decimal places or whole numbers. The use of these smaller sets may be customary or may be the result of explicit agreements among traders.

Four main hypotheses have been used to explain the clustering phenomenon in financial markets: The price resolution hypothesis by Ball, et al. (1985); negotiation hypothesis by Harris (1991), and attraction hypothesis by Goodhart & Curcio (1991) were widely regarded as the three plusible explanations to price clustering. Christie & Schultz (1994) however conducted a study on NASDAQ and attributed collusion of traders as the reason for the avoidance of odd-eighth pricing. After the publication of media reports, Christie, et al. (1994) documented a significant increase in the use of odd-eighth pricing. Clustering has also been explained by the bounded rationality theories as postulated by Simon (1955) and the convenience hypothesis by Mitchell (2001).

1.1.2 Theoretical Explanations for Price Clustering

Researchers provide possible explanations for price clustering in financial markets. First, the existing decimal place-value system encourages individuals to think in groups of ten, or multiples thereof, and encourages a numerousness concept, particularly through the adoption of the place-value system and notation which leads to rounding (Mitchell, 2001). In the marketing literature, cognitive accessibility is the recognized reason for "even-ending" prices. Consumers tend to identify with and process round numbers so these are provided in retail prices and also in real estate listing and transaction prices (Palmon, Smith, & Sopranzetti, 2004). Coupled with this symbolism, mysticism and even cultural convention may dictate some form of basic number preference (Thaler, 1992).

Clustering can also arise due to various behavioural explanations. For example, individuals use simple heuristics, such as anchoring to provide rough approximations in decisions rather than precise estimates (Yule, 1927). There is also a tendency to simplify the information level when mentally processing numbers, which enables quicker and potentially more cost-effective decisions (Preece, 1981). Investigation of numerical stimuli of digits confirms that rounding and fixed formats speed up numerical processing and comprehension and that individuals process even numbers faster than odd digits (Hornik, Cherian, & Zakay, 1994).

There may also be rational economic explanations for clustering. Schelling (1960) suggests that individuals are not simply influenced by the numerical attributes of a decision but tend to use number labels to identify strategies. People may select numbers that they believe others will recognize or which are readily discernible to other parties to facilitate the decision-making process. Humans basically use numbers that they are familiar with, depending on the circumstances (Niederhoffer, 1965). Clustering is also influenced by the acceptable error in decisions based on a cost-benefit trade-off. Individuals in most cases operate in a "sphere of haziness" concerning the value of items and as such, clustering results from attempts to overcome this uncertainty (Loomes, 1988). These explanations lead to the "informational equilibrium pricing" or price resolution/negotiation theory outlined by Ball, et al. (1985) and Harris (1991). Based on this theory, greater precision in prices occurs in order to trade-off the benefits of adopting a more precise price resolution and hence giving a more refined measure of value relative to the increase in costs of acquiring that information and any costs associated with a reduction in the ability to trade rapidly from increased negotiation.

It is also contentious and unlikely that clustering in a financial data series results from a natural order, or alternatively could be a product of the number progression or the number itself as ultimately this depends on the form of the particular series. The idea of a general clustering phenomenon, such as propagated by Benford's law, appears invalid especially for financial data and markets Mitchell (2001). Mitchell argues that any such relationships are (i) restricted to certain data series; (ii) depends on the place digit and (iii) are influenced by the way in which the analysis is conducted and how the clustering is specified, e.g., whether it is relative to a floating or fixed digit place format. This conclusion is contrary to De Grauwe & Decupere (1992), Ley (1996) and De Ceuster, Dhaene, & Schatteman (1998) who suggests Benford's law describes many data series, including financial data, so that widespread clustering simply due to the form of the number itself is possible

1.1.3 Trading on the Nairobi Securities Exchange

Trading of equity securities at the NSE is conducted Monday to Friday in sessions commencing at 9.00 am and closing at 3.00 pm each day. The daily trading sessions are divided into pre-open (9.00 am to 9.30 am), opening auction (9.30 am), continuous trading (9.30 am to 3.00 pm) and close (3.00 pm). Shares are bundled lots of 100 shares and above in the main market boards while shares fewer than 100 are available on the odd lots board. The Main Board is an order-driven market and there are no official market makers for any of the stocks listed on the exchange.

Prior to 2006, buy and sell orders were submitted by telephone to clerks on the trading floor through brokerage firms and orders were matched on the trading floor by open outcry. The conversion of NSE to automated trading was done in 2006. Under the Automated Trading System (ATS), buy and sell orders are transmitted by computer to the Central Depository System (CDS), which electronically matches bids and offers. All orders are submitted in the form of a limit order that automatically expires at the end of each trading day. Orders are executed according to time priority, regardless of their size. Settlement normally occurs on the third business day following a transaction (T+3 Settlement).

The minimum price change stipulated by the NSE follows a graduated schedule across four ranges as shown in Table 1.1 below:

Table 1.1: Minimum Price Change stipulated by the NSE

Below Kshs. 20	Kshs. 0.05
Kshs. 20 -50	Kshs. 0.25
Kshs. 51 -100	Kshs. 0.50
Over Kshs. 100	Kshs. 1.00

The daily price movement for any equity security in a single trading session should not exceed 10% of the equity reference price which is the price calculated and used to establish the opening price of a listed equity security. This restriction does not however apply during major corporate announcements.

1.2 Research Problem

Studies show that price clustering exists in bid, offer and trade prices in equity markets. In the literature, various hypotheses have been proposed to explain the pervasive pattern of price clustering. For example, Aitken, Brown, Buckland, Izan, & Walter (1996) and Aşçıoğlu, Comerton-Forde, & McInish (2007) are consistent with the attraction hypothesis stating the preference of individuals for round numbers. The price resolution hypothesis indicates that if valuation is uncertain, traders may coordinate to restrict the price set to reduce search and cognitive costs (Harris, 1991). Another hypothesis is described by convenience and rounding.

Rounding to convenient numbers seems to be a human habit, as for example when reading scales (Mitchell, 2001). According to Sonnemams (2003), the most plausible explanations for price clustering are the aspiration level hypothesis and the odd pricing hypothesis. The aspiration level hypothesis states that, investors, while buying an asset, already have a target price in mind for which they are willing to sell in the future. These prices are typically round numbers. Odd pricing is the tendency of consumers to consider an odd price like 99.99 as significantly lower than the round price of 100.

No documented study on price clustering is available in Kenya. The closely related studies focus mainly on the efficiency of stock markets which seems to assume that prices follow a random walk model. Both Parkinson (1987) and Dickinson & Muragu (1994) reject the applicability of the random walk hypothesis at the Nairobi Securities Exchange. As an extension to tests on the efficient market hypothesis at the NSE, it is imperative to understand some of the factors like price clustering that cause prices not to follow the random walk model. It has been vastly documented that price clustering is pervasive in financial markets. A sneak peak at the closing prices of listed stocks at the NSE shows that the frequency of prices ending with 0 are common than those ending with 5. This seems to suggest a preference of numbers as postulated by Goodhart & Curcio (1991). This study aims to empirically investigate price clustering at the Nairobi Securities Exchange. The research question that forms the subject of this study is: Does clustering of stock prices exist at the Nairobi Securities Exchange?

1.3 Research Objectives

The main objective of this study was to empirically analyse price clustering on the Nairobi Securities Exchange.

The specific objectives of the research were to analyse the extent of price clustering on the NSE; and to explore the relationship between the observed price clustering and the explanatory variables.

1.4 Value of the Study

The findings of this study are useful to traders, the Nairobi Securities Exchange, the government and the academic community. Traders should now be aware of the rationality behind price discreteness at the NSE. Those who are informed of clustering tendencies may be able to trade at slightly better prices and may be able to place limit orders higher in time/price priority by avoiding the clustering points. According to Mitchell (2001), clustering of prices indicates that traders may believe there is some relevant information in a particular pricing grid or possibly some particular pricing barriers.

The NSE may use the findings of the study to set bidding advances and dealing spreads. According to Harris (1991), traders are usually concerned about the effect of exchange regulations on transaction costs. The current dealing spreads at the NSE is a relatively large percent of the price. The reduction of the same may lead to greater volume and market share.

The government through the Capital Markets Authority (CMA) may use the findings in formulating guidelines towards the management of the capital markets in Kenya. Such guidelines should be aimed at ensuring that clustering of security prices is beneficial to all parties.

Future researchers and academicians who may wish to conduct studies on price clustering in financial markets can dearly benefit from the findings of the study. Currently, there is no documented study of price clustering in any financial market in Kenya. Though studies on security price clustering have been extensive at global level, most of the studies have employed US data (and in particular data from the NYSE). Findings from this study can thus offer good comparative information for future researchers.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to present a review of literature relating to price clustering. Section 2.2 discusses the theoretical literature; Section 2.3 presents the empirical evidence of price clustering from both equity and other financial markets; Section 2.4 discusses the determinants of price clustering as documented by researchers; and Section 2.5 sets out the summary of the literature.

2.2 Theoretical Literature

The literature suggests several hypotheses to rationalize the price clustering phenomenon including the price resolution hypothesis by Ball, et al. (1985), the negotiation hypothesis by Harris (1991), the attraction hypothesis by Goodhart & Curcio (1991), and the collusion hypothesis by Christie & Schultz (1994). Most of the studies on price clustering revolve around these hypotheses.

Other intuitive hypotheses like the convenience, odd pricing and the aspiration levels hypotheses have also been put forward to explain price clustering. The convenience hypothesis was put forward by Mitchell (2001) and asserts that humans prefer rounding to convenient numbers for ease of calculations. Odd pricing on the other hand explains why humans tend to overemphasize the first digits.

2.2.1 The Price Resolution Hypothesis

The price resolution hypothesis asserts that the degree of price resolution is positively related to the amount of information available in the market, and negatively to the level and variability of the asset price. As such, an increase either in the level or in volatility corresponds to an increased probability of observing a higher degree of rounding.

While proposing the price resolution hypothesis, Ball, et al. (1985) observed that price clustering stems from the uncertainty of the underlying value of a given security. A trader will use a fine set of prices if the value is well known. Otherwise, if the value is uncertain, investors may coordinate to restrict the price set to reduce the search and cognitive costs.

2.2.2 The Negotiation Hypothesis

Extending from the price resolution hypothesis, Harris (1991) advances the negotiation hypothesis, arguing that clustering should be considered when analysing the effect of price discreteness on estimators. Harris further proposes that stock price clustering occurs if traders use discrete price sets to lower the cost of negotiation. Therefore, stock price clustering increases with the price level and volatility, and decreases with capitalization and transaction frequency.

The assumption behind Harris' negotiation hypothesis is that clustering for high-price stocks represents the use of discrete price sets that are coarser than the set determined by the minimum price variation (tick size) regulation. This implication results in a higher clustering for the markets with a lower minimum price variation regulation.

2.2.3 The Collusion Hypothesis

The collusion hypothesis proposed by Christie & Schultz (1994) suggests that the structure of multiple dealers in the NASDAQ market is designed to produce narrow bid-ask spreads through the order-flow competition among individual dealers.

According to them, price clustering in stock markets reflects dealer collusion intended to maintain wider bid-ask spreads than would prevail under full competition. Thus, as bid-spread spreads increase, so does the degree of price clustering in the security.

2.2.4 The Attraction Hypothesis

The attraction hypothesis proposed by Goodhart & Curcio (1991) suggests that individuals have a preference for round numbers and therefore they like to trade with round numbers prices. Studies that have been conducted to test the attraction hypothesis document that individuals are more attracted to quotes ending in 0 or 5 followed by even numbers. Odd numbers fall down the pecking order of "attractive numbers".

Against the above explanation is the fact that in other situations round numbers are typically not preferred: the favourite numbers in lotteries are 'lucky' numbers like birthdays and the most popular number: ‘7’ and not the round numbers (Mitchell, 2001). However, numbers in lotteries are not quantities; nobody has to make calculations with their lotteries numbers.

2.2.5 The Convenience and Rounding Hypothesis

The convenience and rounding hypothesis avers that round calculations with round numbers are easy to perform since it limits informational load and decreases the probability of costly mistakes. Rounding to convenient numbers seems to be a human habit, for example when reading scales (Mitchell, 2001).

However it is noteworthy that in financial transactions the risk of mistakes is not very high (a limit order by telephone is always repeated by the bank employee and when internet is used a confirmation screen is common). Convenience and rounding may be an explanation for price clustering on the level of whole numbers versus fractions, but for the clustering on round whole numbers it is less plausible because the cost of rounding would be substantial.

2.2.6 The Odd-Pricing Hypothesis

Odd-pricing (also called odd-ending pricing or just-below pricing) is a phenomenon which is common in the marketing literature and cognitive psychology. This type of pricing is widely used in marketing of consumer goods and means that the price is just below some round number (for example Kshs. 9.99 instead of KShs.10.00). Many consumers tend to consider the odd price as significantly lower than the round numbered price.

Humans may process and store numerical information in a way that the first digits, which contain more significant information than later digits, are treated as more valuable information. To compare two numbers, a left-to-right comparison (first compare the hundreds, if these are the same the tens, etc.) is a very efficient procedure.

The human tendency to overemphasize the first digits can also be observed in time measurement. Passing from an age of 39 to 40 is considered by many as a bigger step than for example from 38 to 39 or from 40 to 41. In a financial market it would mean that a stock price of 100 would be considered (much) higher than a price of 99.9. A seller will be relatively happy to sell at 100 (and more limit sell orders will be placed at 100) while a buyer would be reluctant to pay a price that is not in the 90s but in the 100s (Sonnemams, 2003).

2.2.7 The Aspiration Level Hypothesis

The aspiration level hypothesis was derived from the bounded rationality theories. One of the contributors to these theories, Simon (1955) introduced the satisfying decision maker who does not try to maximize some utility function but instead looks for a 'good enough' solution.

Some investors, when buying a security, already have a target price in mind for which they are willing to sell the security in future. For instance, an investor who buys a stock for Kshs. 9 may expect the price of this stock to rise in the future to Kshs. 50.

The target price (and the associated gain) in Simon's sense is considered an aspiration level. Studies by Hornik, et al. (1994) show that target prices always seem to be round numbers. This will lead to relatively many limit sell offers to be posted at round whole numbers.

2.3 Empirical Literature

Price clustering has been documented in various equity markets. Osborne (1962) presented the first rigorous empirical evidence of 'congestion' in US share prices. Congestion means that "there are price ranges in which a given stock price spends an inordinate amount of time". In the absence of clustering, we would expect to see a uniform distribution over admissible prices. Instead, Osborne found a "pronounced tendency for (closing) prices to cluster on whole numbers, halves, quarters, and odd one-eighths in descending preference".

Niederhoffer (1965) documented clustering of limit orders taken from the order book of a specialist on the NYSE. The ratio of limit order closing prices at the even eighths (0, 2, 4, 6) to those at the odd eighths (1, 3, 5, 7) was 8.8:1, of which prices at whole numbers (0 eighths) constituted 7.7:1. Niederhoffer found clustering in the closing prices of actively and inactively traded shares, in high and low-priced shares, and in noon as well as closing prices. Higher-priced issues traded mostly at the integers, while stable, lower-priced issues settled at even numbers of eighths. Niederhoffer argued that the auction market mechanism ensured that price changes show regularity and structure, because of behavioural preferences and specialist trading strategies. He suggested that clustering was the result of the tendency of stock market participants to place their orders at "numbers with which they are accustomed to deal", such as whole and round numbers. These findings led him to conclude that such structure and regularity to prices casts serious doubt on the premise that share prices are random. Specialists and floor traders had indicated to him that the congestion of limit orders opens up a lucrative trading technique. The example he cited was a share that recently rose from 1/8 to 7/8. There would probably be few buy limits below 7/8, and numerous sell limits one tick higher (at 8/8). The specialist could sell short at 7/8, hoping to drive the price back to 1/8 and make a profit, while feeling relatively safe in the knowledge there should be ample time to cover for a 1/8 loss if price were to rise further. A similar trading opportunity might arise if price had recently declined. Niederhoffer speculated that this strategy could explain the Osborne (1962) observation that there were more highs than lows at 7/8 and fewer highs than lows at 1/8.

Niederhoffer (1966) used trades data for seven days chosen randomly from the complete record of ticker transactions in 1964 for NYSE stocks. Prices were grouped into three strata: (i) 1,000 cases where price was unchanged from the previous trade; (ii) 12,800 cases where it changed by one-eighth; and (iii) 11,000 cases where it changed by more than one-eighth. He found that 58.5% of all trades were at an even eighth, and that clustering at an even eighth was most pronounced in the third stratum. Niederhoffer argued that the clustering he observed was a consequence of more limit and stop orders being placed on specialists' books at even eighths. Price cannot move from or through such a position until all relevant orders have been exhausted. Hence there is the tendency for 'stickiness' at even eighths.

Niederhoffer & Osborne (1966) documented additional properties of dependence in the NYSE ticker prices of six Dow Jones stocks traded in October 1964. While the random walk model states that changes in the price of consecutive transactions are distributed independently, Niederhoffer and Osborne found strong evidence of dependence. For example, after a price rise, then it was more likely that the next price change would be a decline; similarly, a decline would be more likely to be followed by a rise. In addition, after two changes in the same direction, the odds of a continuation in the same direction was almost twice as great as after two changes in opposing directions. Their data displayed once again the "stickiness of even eighths". They found that "reversals are relatively more concentrated at integers where stable slow-moving participants offer to buy and sell. There is a concentration of particular types of reversals just above and below these barriers."

Harris (1991) later gathered evidence from the NYSE to show that stock price clustering had persisted through time and that it conformed to the same hierarchy of degrees of rounding that had already been noted by other researchers. Building on Ball et al. (1985) – who postulated the price resolution hypothesis – Harris posited that there are factors that cause the desired price resolution to become more coarse, and hence the extent of clustering to increase in certain circumstances. He suggested that price clustering occurs because traders use a restricted set of prices to simplify their negotiations, which makes them less costly. The existence of a restricted set of discrete prices that is known to all traders' means that negotiation time is reduced, since it limits the number of different prices at which bids and offers will be made. It also limits the amount of information exchanged between traders. Consequently bid and offer prices converge more rapidly, and the time savings alone can be significant. Cross-sectional variation in price clustering was examined by relating its frequency to individual stock price attributes. The attributes Harris selected were volatility, firm size, transaction frequency, price level and whether the stock is traded primarily on a dealer market. Multivariate regressions were fitted across individual stocks, using two different measures for the dependent variable to summarize price clustering in each stock. Clustering was found to increase with the stock's price level and volatility, and to decrease with firm size and transaction frequency. It was also more prevalent in a dealer's market.

An intense discussion about price clustering started when Christie & Schultz (1994) found that NASDAQ market makers avoided odd-eighth quotes for 70 of 100 large, actively traded NASDAQ securities, including Apple Computer and Lotus development (and seemed to implicitly collude to keep the spread at least 25 cents). The authors compare the dollar spreads for the NASDAQ and NYSE/AMEX stocks and find a systematic difference in the frequency of odd-eighth spreads in the two pools. Their finding was that larger trades are far more likely to occur on odd-eighth spreads than smaller trades. This led them to rule out the negotiation hypothesis in explaining the clustering phenomena. Next, the authors used logistic regression analysis to determine that economic determinants such as volume, volatility, market capitalization, and stock price do not play a role in predicting the probability that stocks are quoted using odd eighths. By elimination, the authors conclude that the only remaining hypothesis explaining the absence of odd-eighth spreads for NASDAQ securities is tacit collusion among market makers. After media exposure of the article, Christie, et al. (1994) observes a drastic increase of odd-eighth pricing.

Another study on price clustering was conducted by Aitken, et al. (1996) at the Australian Stock Exchange (ASX). Much of the data used in their analysis was sourced from the complete set of SEATS transactions obtained from the ASX. A separate database was constructed from the raw data, comprising observations on the ordinary fully paid shares of the 267 listed companies that traded at least five times per day, on average, during the period

3 September 1990 to 3 September 1993 (inclusive). The objective of the study was to document the clustering effects at the ASX including the extent as well as the association between clustering and the informational uncertainty as modelled by Harris (1991). As expected, the researchers found that price clustering is strongly manifest in normal trades on the ASX after the market opens. Further, clustering increased with the price level, market volatility, own stock volatility, trade size, and the size of the bid-ask spread. It decreased with trading

Grossman, Miller, Cone, Fischel, & Ross (1997) examined price clustering on the London Stock Exchange using all inside quotes posted during October 1994 on the Stock Exchange Quotation System (SEAQ) for liquid stocks. They found that the frequency of clustered pricing on the NASDAQ is comparable to other financial markets such as gold and foreign exchange, but not the NYSE. The authors contend that the lack of price clustering on the NYSE is a result of the race among investors, who place limit orders to compete with the best market orders, and the specialists.

Hameed & Terry (1998) examined the impact of tick size on price clustering and trading volume on the Stock Exchange of Singapore (SES) between January 1980 and July 1994. One of the main findings was that price clustering is found to increase when the tick size decreases. Unlike Harris, they did not find a consistent relationship between price clustering and stock price volatility. Clustering was found to be inversely related to tick size, especially for higher priced stocks, once the other variables were controlled for.

Vogt, Bodo, Uphaus, & Albers (2001) studied the stock price clustering phenomenon in the context of numerical perception and response while Huang & Stoll (2001) analysed transactions data of stocks traded on the London Stock Exchange (a dealer market) and also traded as American Depository Receipts (ADRs) on the New York Stock Exchange (an auction market). They concluded that market characteristics (e.g. clustering and tick size) are endogenous to the market structure. But the effect of price clustering is not limited to special stock exchanges.

Sonnemams (2003) studied stock price clustering using data from the Dutch stock market. In the study, two competing hypotheses - the aspiration level hypothesis and the odd price hypothesis - were tested, using data from the Dutch stock market for the period 1990 to 2001. The findings of the study were consistent with the odd price hypothesis.

Aşçıoğlu, et al. (2007) examined price clustering on the Tokyo Stock Exchange. The researchers found that prices ending in zero were more popular than those ending in five. In view of the fact the TSE has no market makers, and direct negotiation between traders, both the collusion and negotiation hypotheses were rejected as explaining the clustering. Instead, their evidence showed support for the attraction hypothesis

Clustering of prices has also been documented in other financial markets including gold and foreign exchange markets. Ball, et al. (1985) investigated the morning and afternoon fixing prices of gold on the London market from 2 January to 30 April 1981, when the price of gold was unusually volatile. They hypothesized that price clustering depends on how well the asset's underlying value is known. If value is not well known, prices will cluster. If value is well known, traders will use a finer set of prices. The maximum precision of pricing (tick size) in the London gold market is five cents US dollars. Their findings showed that there was clustering in the fixing price, providing clear evidence that the level of rounding is higher than the minimum price tick. The degree of price resolution (rounding) is not constant over time, but rather it changes depending on the amount of information in the market. Rounding increases with the level and volatility of price.

Goodhart & Curcio (1991) examined price clustering in the foreign exchange market. The two tested the attraction hypothesis as argued by Harris (1991) and the price resolution hypothesis which was proposed by Ball, et al. (1985). In the context of their study, they hypothesized that the final digit of the underlying value is uniformly distributed over the integers 0 to 9. According to the attraction theory, 1 and 9 would be strongly attracted to 0, 5 would be the next common final digit, followed by (2 and 8), (3, 7, 4, 6) and finally (1 and 9). Harris (1991) in fact rejected the attraction theory because he found the frequencies of odd-eighths (1, 3, 7 and 9) were approximately the same. The study by Goodhart & Curcio (1991) found out that, while Forex bid and ask prices quoted by foreign exchange dealers and bankers tended to cluster, the clustering did not carry over to the penultimate digit. They concluded that clustering in the final digit depends on the desired degree of price resolution by traders. However, clustering in the amount of the bid-ask spread appears to be driven by a separate behavioural pattern, consistent with the pure attraction hypothesis.

No study on price clustering has been conducted in Kenya. Closely related studies have focused on the efficiency of the Nairobi Securities Exchange (NSE) and investor irrationality at the NSE. The efficient market hypothesis assumes that prices reflect all the available information, and that prices follow a random walk model. One of the studies focusing on market efficiency on the NSE was conducted by Parkinson (1987) who tested the validity of the weak-form efficiency of the Nairobi Stock Exchange (NSE) using monthly prices of individual companies for the period 1974 to 1978. The findings of the study concluded that stock prices at the NSE do not follow the random walk model.

A similar study on the NSE was conducted by Dickinson & Muragu (1994). They created a database of weekly prices over ten years of the 30 most actively traded equities on the Nairobi Stock Exchange and failed to find evidence inconsistent with weak-form efficiency in the stock exchange by means of both runs tests and Q-test statistics. Several other studies to test the efficiency of the NSE have been conducted. While other studies suggest that the market shows the weak-form efficiency, most of the studies conclude that the NSE is not efficient, and consequently stock prices do not follow a random walk model.

2.4 Determinants of Price Clustering

Various empirical studies have linked the price clustering phenomenon to information uncertainty. Four proxies - market value, stock price, return volatility, and trading activity - are normally used to evaluate the information uncertainty (Harris, 1991).

According to Easley & O'Hara (1987), larger orders are sometimes associated with informed agents and their placement should lead to greater clustering. Furthermore informed traders placing large orders may wish to hide their knowledge by quoting a more clustered price. The trade size is measured by the natural logarithm of the dollar value of the trade. Clustering of stock prices is also expected to increase with increase in return volatility which will be measured by the standard deviation of weekly return estimated over the period of the study.

Other than the trade size and volatility, stock price and liquidity are the other proxies of price clustering. Assuming the number of issued (outstanding) shares is known, the degree of clustering should be proportional to stock price to a first approximation. Liquidity is associated with efficiency in price discovery in the sense that the more liquid the stock is, the more precisely its value is known, and the less likely its price will cluster. Liquidity is proxied by the natural logarithm of trading frequency, defined as the average number of trades per trading day for that stock over sample period

2.5 Summary

Following the insights of these studies, it is clear that stock price clustering is not an effect specific to a special market environment and thus not specific to the market rules. Rather it does seem, as if it is an underlying effect caused by human decision processes. It is also true that price clustering varies across exchange types.

There is currently no literature on clustering in African countries. Most of the literature on share price clustering has employed US data, in particular data from the NYSE specialist market. Studies have also been conducted in the Australian Stock Exchange, London Stock Exchange, Amsterdam Stock Exchange, Taiwan Stock Exchange, the Stock Exchange of Singapore (SES) and other leading stock exchanges. Kenya is regarded as one of the emerging countries, and has an equally developed stock market, the Nairobi Securities Exchange (NSE).The NSE is currently the fourth largest bourse in sub-Saharan Africa and is purely order driven. The availability of stock price data for many firms of varying characteristics provides an excellent opportunity to study discrete pricing at the NSE. The findings of this study will provide good comparative information for other researchers wishing to conduct studies on clustering.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter sets out the methodology that was adopted in the study. Section 3.2 presents the research design; Section 3.3 presents the population and sample; Section 3.4 discusses the data and data collection instruments; and Section 3.5 presents the data analysis including data validity and reliability analysis.

3.2 Research Design

This research employed a descriptive design since it sought to analyse the extent of price clustering on the NSE and explore the relationship between the observed price clustering and the explanatory variables as modelled by Harris (1991). According to Greener (2008), descriptive research studies are meant to obtain pertinent and precise information relating to the current status of phenomena and where possible draw a valid general conclusion from the facts discovered. The extent of price clustering on the NSE was determined using the frequency of the last digit of share prices and correlation analyses were used to explore the relationship between price clustering and the explanatory variables.

3.3 Population and Sample

This section presents the population and sample that was used in the study. Section 3.3.1 covers the population of the study and Section 3.3.2 presents the sample.

3.3.1 Population

Greener (2008) defines a population as the full universe of people or things from which the sample is selected. The population of this research consisted of all the stocks that were listed on the NSE between January 2009 and December 2013. As at December 2013, sixty one (61) stocks as detailed under Appendix 1 were listed on the NSE.

3.3.2 Sample

Sample is the section of the population chosen for the study (Greener, 2008). In this research, a sample comprising of observations on the ordinary fully paid shares of the sixty one listed companies that traded at least three times per day, on average, during the period under study was selected. Only regular trades transacted in the five and half hours of Normal Trading Mode were considered in this research. Opening trades were excluded, because they are transacted at an averaged price. The averaging process contrasts with the discrete tick size rules that govern admissible prices when the buyer and seller place their orders. Any trades that took place after the close of Normal Trading Mode, that is, after 3 pm were also excluded.

3.4 Data and Data Collection Instruments

The study employed secondary data from the Nairobi Securities Exchange (NSE). The data included each regular trade's price, and volume, and the price of the highest limit order bid and lowest limit order ask immediately before the trade from January 2009 to December 2013.

3.5 Data Analysis

The data analysis in this study focussed on identifying the extent of price clustering on the NSE and exploring whether the observed phenomenon could be explained by the price resolution hypothesis. The model used in this study was based on that used by (Harris, 1991). Section 3.4 sets out the conceptual model and defines the variables whereas Section 3.5.2 presents the analytical model. Diagnostic tests that were conducted to ascertain the data validity and reliability have also been explained under Section 3.5.2.

3.5.1 Conceptual Model

To explore whether price clustering at the NSE can be explained by the price resolution hypothesis, the study used a model used by Harris (1991). The following four independent variables were used: stock price (P); market capitalization (MV); number of trades (T), and stock return volatility (σ). The conceptual model used by Harris is shown below:

$$\text{Price clustering } (X) = f\,[\text{stock price } (P), \text{ market capitalization } (MV), \text{ number of trades } (T), \text{ stock return volatility } (\sigma)] \qquad (1)$$

Adapted from “Stock price clustering and discreteness” by L. Harris, 1991, *Review of Financial Studies*, 4, 389 – 415.

With the exception of stock return volatility, the estimates for each stock were obtained by averaging the estimates across trading days. Volatility was obtained by calculating the standard deviation of stock returns across the trading days. Finally, means were obtained by averaging the means of each stock across all stocks.

3.5.2 Analytical Model

The analytical model was based on the model proposed by Harris (1991) as shown below:

$$X = \beta_0 + \beta_1 \ln(P) + \beta_2 \ln(T) + \beta_3 \ln(\sigma) + \beta_4 \ln(MV) + \varepsilon \qquad (2)$$

Where:

X is the degree of price clustering which was measured by the frequency of the last digit of price. P is the average stock price, T is the average number of trades, σ is the standard deviation of stock return, and MV is the market value.

$\beta_0, \beta_1, \beta_2, \beta_3$ and β_4 are regression coefficients

The above analytical model was solved using a multivariate regression analysis.

The Pearson‘s correlation coefficient was used to test the relationship between the variables. If the correlation is positive, a positive relationship is inferred. If it is negative, the relationship is negative. The p-values were used to test the significance of correlation between the variables.

The test for multicollinearity was conducted using the Variance Inflation Factors (VIF) and Tolerance Values. The models significance was established using the F-statistic and the p-values from the ANOVA table.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the data analysis, results and discussion of the research. The summary statistics of the research are covered under Section 4.2; the trend analysis of the variables under Section 4.3; the correlation statistics of the price clustering determinants on the NSE under Section 4.4; the tests for multicollinearity of the variables under Section 4.5; and the regression results under Section 4.6.

4.2 Summary Statistics

Table 4.1 below presents the descriptive statistics for Stock volatility, Price Clustering, Price of Shares, Number of Trades and the Market Capitalization. The table shows that investors preferred stocks whose prices ended with fives. The mean value for price clustering was approximately 5, indicating they were the most preferred share prices. From Table 4.1, it can also be observed that shares whose prices ended with five were most preferred given that it appeared 38,441 representing 67.88% of the total observations. On the other hand, the least preferred share price was that ending with three as they only appeared 1,733 times, accounting for 3.06% of the total observations.

Table 4.1 also indicates that the mean prices of the shares for the stocks quoted at the NSE during 2009-2013 period had a mean of 59.41 with the maximum traded share value during this period being 600 and the minimum share value being 1.425. The stock volatility which was computed from the average price of the share prices had a mean of 8.256 and standard deviation of 11.07 over the same period.

The market capitalization for the NSE quoted firms over the period of study had a mean of 7,923,186 with a standard deviation of 40,231,145. On the other hand the number of shares on average was approximately 37 and the number of trades averagely deviated by approximately 76.

Table 4.1: Descriptive Statistics 2009-2013

	Clustering	Price	Stock Volatility	Market Capitalization	No. of Trades
Mean	4.787717	59.41830	8.256074	7,923,186.	36.62479
Median	5.000000	23.37500	3.822437	692,112.5	13.00000
Maximum	9.000000	600.0000	74.01389	5.99E+09	8,838.000
Minimum	0.000000	1.425000	0.144928	33.50000	1.000000
Std. Dev.	1.778294	79.17997	11.07729	40,231,145	75.70866
Observations	56,632	56,632	56,632	56,632	56,632

Source: Nairobi Securities Exchange, 2009 – 2013

Table 4.2 below presents the frequency with which the last value of the share price was observed for the stocks quoted on the NSE over the five year period of study. The results indicated that there is a high preference for shares trading in multiples of five, followed by stocks whose share price ended with the number zero. The least preferred share price by investors as indicated by the frequency in Table 4.2 below was share prices that ended with the number three.

Table 4.2: Frequency of Price Clusters

Count of Clustering	**Total**	**Percent**
0	2,576	4.55
1	1,950	3.44
2	1,908	3.37
3 Least Preferred Share Price	1,733	3.06
4	2,051	3.62
5 Most Preferred Share Price	38,441	67.88
6	2,103	3.71
7	1,824	3.22
8	2,036	3.60
9	2,010	3.55
Grand Total	**56632**	**100.00**

Source: Nairobi Securities Exchange, 2009 – 2013

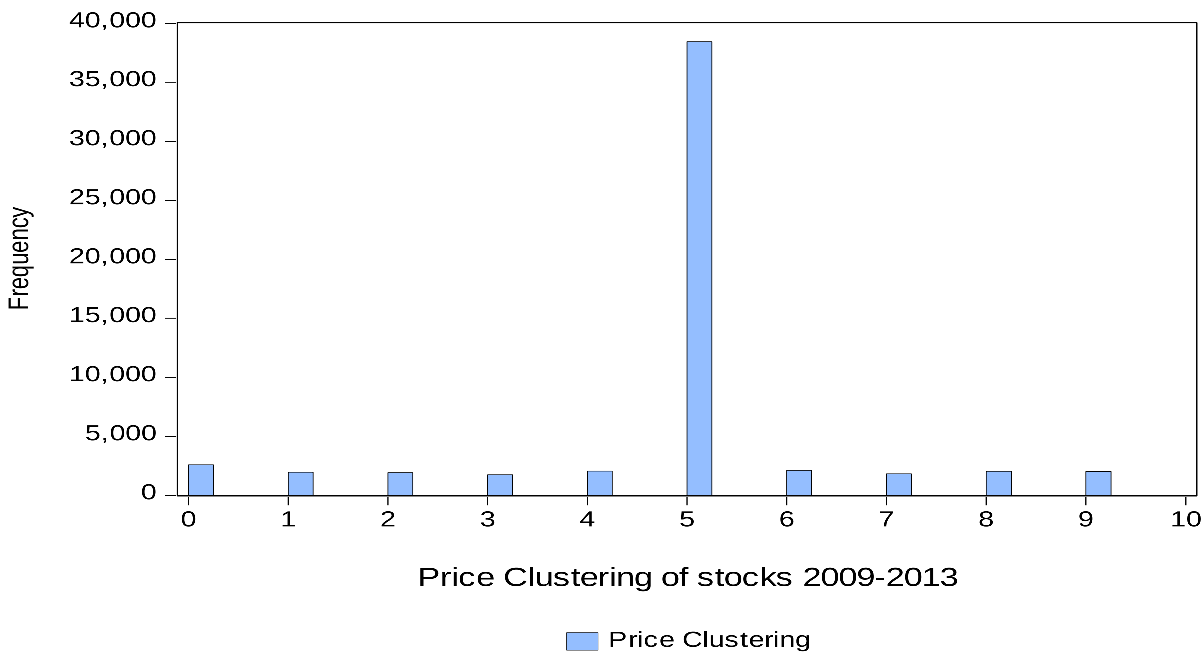
4.3 Trend Analysis

This section presents the general behaviour of the study variables over the period of study. The trends in Stock Volatility, Market Capitalization, Stock Prices, Number of Trades as well as Price Clustering are also presented.

4.3.1 Price Clustering

An analysis of price clustering for the stocks quoted at the NSE indicated that investors have preference for shares whose price ends with the digit five as indicated in Figure 4.1 below. Table 4.2 above indicated that 67.88 percent of all stock prices (38,441 trades) have five and 4.55 percent of all stock prices have (2,576 trades) have zero as the last digit. This shows that 72.43 percent of all observations have a digit of 0 or 5 as the last digit.

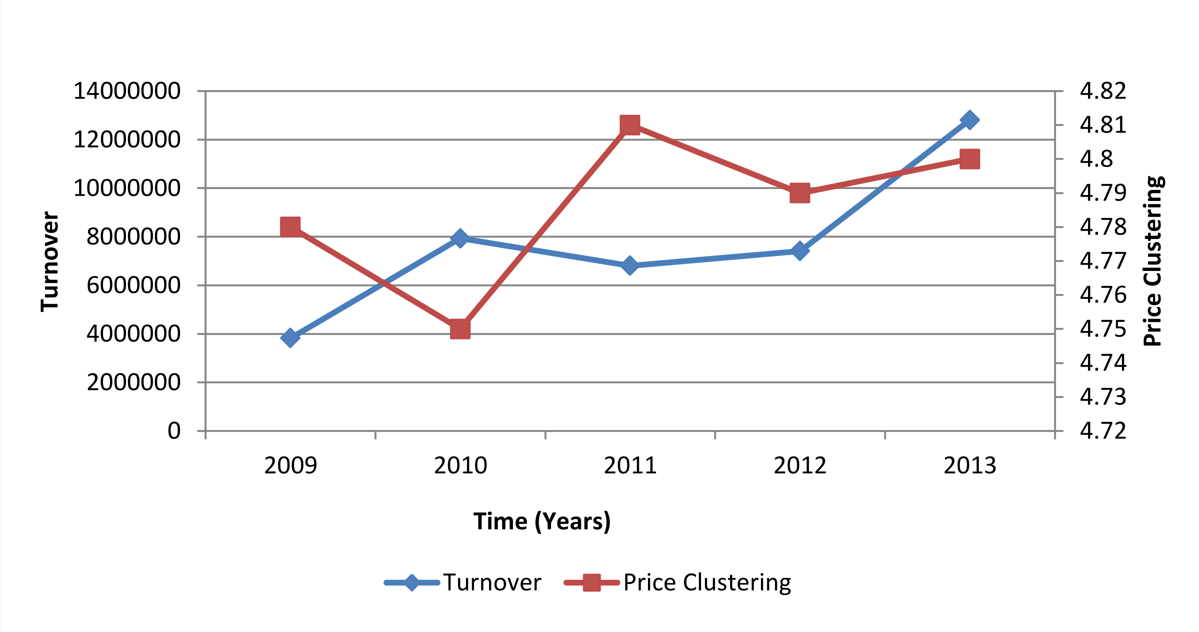
Figure 4.1: Price Clustering of Stocks 2009-2013



4.3.2 Turnover and Price Clustering

Figure 4.2 below shows the turnover and price clustering movements for the period of the study, 2009 - 2013. It can be concluded that the Turnover and Price Clustering of stocks for the companies listed at the NSE move in the same direction (i.e. their stock turnover has been increasing over time as has been the price clustering of the stocks).

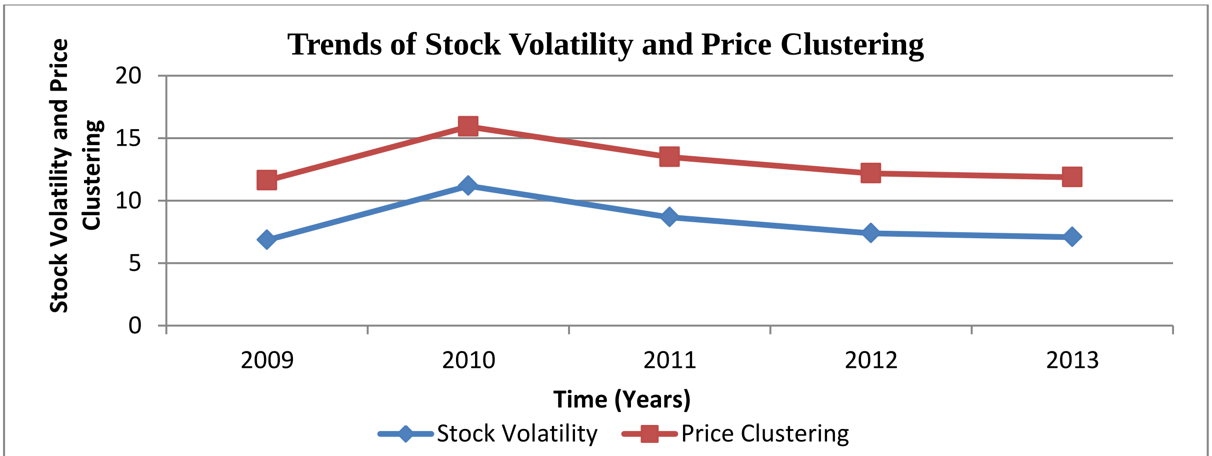
Figure 4.2: Trends in Turnover and Price Clustering 2009-2013



4.3.3 Stock Volatility and Price Clustering

Figure 4.3 below shows the stock volatility and price clustering of the shares traded for the period 2009-2013 at the NSE. The figure shows that stock volatility and price clustering have been moving in the same direction. For instance, during the period 2009-2010 the stock volatility increased and there was also an increase in the price clustering in the stocks during the same period. For the period 2010-2013, the stock volatility has been on the decline as exhibited in the Figure 4.3 below. This was also the case with price clustering. It can thus be concluded that stock volatility has been moving in the same direction with price clustering.

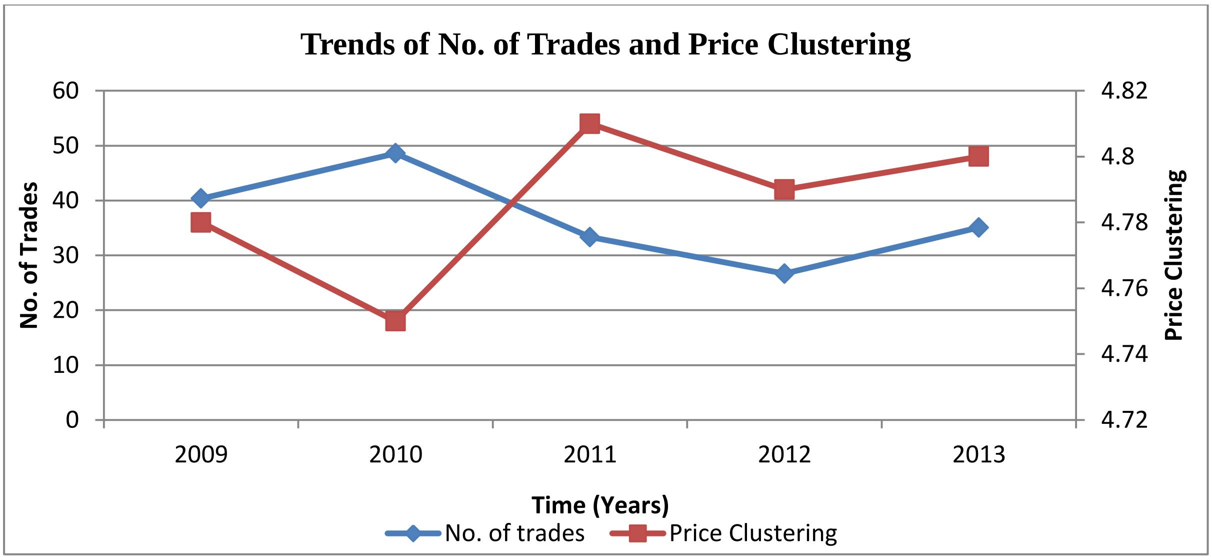
Figure 4.3: Trends in Stock Volatility and Price Clustering 2009-2013



4.3.4 Number of Trades and Price Clustering

Figure 4.4 below shows the movements of the frequency of trading in stocks with price clustering. For the period 2009-2010 there was a negative relationship between Frequency of trade and price clustering. For instance, as the frequency of trades increased, price clustering was on the decline. The figure also shows that for the period 2010-2013, the frequency of trades in stocks has been on the decline with a slight increase from 2012 to 2013. Over the period 2010-2011 price clustering has been on the rise but was accompanied by a decline in the period 2011-2012 and thereafter a slight increase from 2012-2013. It can thus be inferred that as the frequency of trading increases, the observed price clustering behaviour diminishes.

Figure 4.4: Number of Trades and Price Clustering Trend Analysis 2009-2013



4.4 Determinants of Price Clustering on the NSE

Table 4.3 below shows the correlation matrix of price clustering, no. of trades (deals), turnover, and stock volatility. The correlation matrix shows that clustering and price have an inverse relationship (r = -0.147959) and is statistically significant at 5 percent (p-Value = 0.0000). This implies that as the last digit of the stock price increases from 0 to 9, price clustering reduces. As indicated by the frequency of the last digit of stock prices in Table 4.2, stocks whose prices ended with 0 and 5 were preferred and other numbers such as 2,3,4,6,7,8,9 were not as preferred as 0's and 5's. The correlation table (Table 4.3) also indicates that clustering and number of trades (Deals) have a positive relationship (r = 0.043706) and the observed relationship is significant (p-Value = 0.0000). The implication of this is that as the number of trades increases the price clustering as captured by the last digit of the stock price also increases.

Turnover and price clustering relationship is observed to have a positive relationship (r = 0.000668). However, this relationship is insignificant at 5 percent (p-Value = 0.8736). This finding is consistent with Easley & O'Hara (1987) who suggested that market players tend to wait in order to observe the trading behaviour of agents who are perceived to be informed before placing their orders.

On the other hand, stock volatility and price clustering are observed to exhibit a negative relationship (r =-0.101316) and that the relationship is significant (p-Value = 0.0000). This implies that, the more volatile stocks are, the less the observed price clustering of stocks.

Table 4.3: Correlation Matrix 2009-2013

	Clustering	Price	Deals	Turnover	Stock Volatility
Clustering	1.0000 -----				
Price	-0.147959 (0.0000)	1.0000 -----			
Deals	0.043706 (0.0000)	-0.188329 (0.0000)	1.0000 -----		
Turnover	0.000668 (0.8736)	0.061434 (0.0000)	0.255317 (0.0000)	1.0000 -----	
Stock Volatility	-0.101316 (0.0000)	0.717926 (0.0000)	-0.089770 (0.0000)	0.038219 (0.0000)	1.0000 -----

Source: Nairobi Securities Exchange, 2009 – 2013

4.5 Test for Multicollinearity

The classical linear regression assumption requires that the independent variables should not be correlated. The test for multicollinearity was therefore conducted using the variance inflation factors (VIF) and the tolerance levels. Variance Inflation Factors (VIF) measures how much the variance of the estimated coefficients is increased over the case of no correlation among the independent variables. If no two independent variables are correlated, then all the VIFs will be 1. If there are two or more variables that will have a VIF around or greater than 10, any VIF value that exceed 10 indicates the existence of multicollinearity. On the other hand, the Tolerance level value should be greater than 0.10 and any Tolerance value less than 0.10 indicates a collinearity problem. Table 4.4 below presents the Tolerance and VIF values. The VIF values as indicated in the table show that all the values are below 10 as is also the case with Tolerance values which are above 0.10. This therefore implies that the No. of Trades (Deals), Market Capitalization, Stock Volatility and Price do not suffer from multicollinearity.

Table 4.4: Test for Multicollinearity

Variable	Collinearity Statistics	
	Tolerance	VIF
No. of Trades (Deals)	0.717	1.396
Market Capitalization	0.733	1.365
Stock Volatility	0.472	2.117
Price	0.452	2.210

Source: Nairobi Securities Exchange, 2009 – 2013

4.6 Regression Results

This section presents the model summary results, ANOVA Table and the regression results obtained for the model.

4.6.1 Model Summary Results

Table 4.5 below presents the model summary of the regression results. The correlation between the variables is 0.40. The table also indicates that the R-square of the model and in this case the No. of Trades (Deals), Market Capitalization, Stock Volatility, and Price accounted for 15.9 % of the variance in price clustering for stock prices quoted on NSE for the period 2009-2013.

Table 4.5: Model Summary

Model	R	R Square	Std. Error of the Estimate
	0.40	0.159	1.756

Source: Nairobi Securities Exchange, 2009 – 2013

4.6.2 Goodness of Fit for the Model

The goodness of fit of a model can be inferred from the ANOVA table. The ANOVA table tests whether or not the model significantly explains the outcome variable, which in this case is price clustering. Table 4.6 below shows that the model is significant in explaining price clustering of stocks quoted on the NSE (p-Value = 0.000)

Table 4.6: ANOVA Table

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	4,539.427	5	907.885	294.534	0.000
Residual	174,546.509	56,626	3.082		
Total	179,085.936	56,631			

Source: Nairobi Securities Exchange, 2009 – 2013

4.6.3 Multivariate Regression Model Results

A multivariate regression was conducted where price clustering was regressed against the Number of Trades (Deals), Market Capitalization, Stock Volatility, and Price and the results are presented in Table 4.7 below. The overall model was significant, F (5, 56626) = 294.534, p-Value = 0.000, and accounted for 15.9 % (R^2 = 15.9) of the variance in price clustering.

The results indicated that the No. of trades (Deals) was a significant predictor of price clustering (p-Value = 0.003). The No. of trades coefficient was negative (β = -0.014) implying that as the number of trades increased the tendency of prices to cluster around some value decreased. Market Capitalization was also a significant predictor (p-Value = 0.000) and exhibiting a positive relationship (β = 0.062) with price clustering. This implied that as the market capitalization of a company's stocks increased, there was an associated tendency of prices to cluster. Stock volatility was an insignificant predictor of price clustering (p-Value = 0.14). On the other hand, price was a negative (β = -0.165) and significantly (p-Value = 0.000) related to price clustering. A dummy for the years was also included in the model and the results in Table 4.7 indicated that it was a positive (β = 0.016) and significantly (p-Value = 0.000) related to price clustering. This implies that the tendency of prices to cluster increased over time.

Table 4.7: Multivariate Regression Model

	Un-standardized Coefficients		Standardized Coefficients	t	sig
	B	Std. Error	Beta		
Constant	4.364	0.046		95.878	0.000
No. of trades (Deals)	0.000	0.000	-0.014	-2.953	0.003
Market Capitalization	0.044	0.003	0.062	12.707	0.000
Stock Volatility	0.001	0.001	0.009	1.475	0.140
Price	-0.004	0.000	-0.165	-26.802	0.000
Dummy Year	0.020	0.005	0.016	3.769	0.000

Note. F (5, 56626) = 294.534, p-Value = 0.000, R^2 = 0.159

Source: Nairobi Securities Exchange, 2009 – 2013

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter presents a summary of the study, conclusions, study limitations and recommendations. The summary of the study is covered under Section 5.2; conclusions in Section 5.3; limitations of the study in Section 5.4; and recommendations in Section 5.5 and 5.6. The recommendations under Section 5.5 sets forth the recommended course of action to investors based on the study findings for possible implementation, whereas that under Section 5.6 outlines the suggestions for further study.

5.2 Summary of the Study

The study findings indicate that stocks whose prices end with digit 5 are most preferred accounting for 67.88 percent of price clustering (38,441 observations) over the period of study. Following the preference, was stock prices ending with digit 0 (2,576 observations) accounting for 4.55 percent of the total stock prices. The preference of stock prices were then followed by stocks prices whose last digits ended with 6, 4, 8, 9, 1, 2, 7, and 3.

The test for multicollinearity revealed that the VIF and Tolerance values were below 10 and greater than 0.10 respectively and therefore the predictor variables (No. of Trades, Market Capitalization, Stock Volatility, and Price) did not suffer from multicollinearity.

The regression results revealed that 15.9 percent of the variance in price clustering was explained by No. of Trades, Market Capitalization, Stock Volatility, and Price. The overall mode was also established to be significant in explaining the observed relationship.

5.3 Conclusions

The study results showed that price clustering is evident on the NSE as revealed by the frequency of occurrence of the last digit of stock prices. Most stock prices were clustered around the digit 5 given that the frequency of occurrence of the digit was 67.88 percent of the total stocks examined for the period 2009-2013. This finding is in line with previous studies which have documented clustering of stock prices around some numbers including the findings of Niederhoffer (1965) who documented clustering of limit orders which were taken from the order book of a specialist on the NYSE. The finding however differs from that of Ascioglu, et al. (2007) who found that prices ending in zero were more popular than those ending in five at the Tokyo Stock Exchange.

The study found that the No. of trades (Deals) to be positive and significantly related to price clustering (β = -0.014, p-Value = 0.003). This finding is consistent with Aitken, et al. (1996) who also found that price clustering was strongly manifested at the Australian Stock Exchange (ASX). Aitken, et al. (1996) found that clustering increased as the trade size increased. Similarly this finding is inconsistent with Harris (1991) who found price clustering to decrease with transaction frequency.

Market Capitalization was also a significant predictor (p-Value = 0.000) and that it exhibited a positive relationship (β = 0.062) with price clustering. It was thus concluded that price clustering was more observed as the market capitalization of the firm increased. Stock volatility was an insignificant predictor of price clustering (p-Value = 0.14). This finding is consistent with that of Hameed & Terry (1998) who did not find a consistent relationship between price clustering and stock price volatility. Similarly, this finding is inconsistent with that of Harris (1991) on the Australian Stock Exchange (ASX). According to Harris (1991), price clustering was found to increase with the increase in the stock volatility.

The study also concluded that price was negative (β = -0.165) and significantly (p-Value = 0.000) related to price clustering. This finding is in agreement with that of Harris (1991) who found the evidence of price clustering to increase with the stock's price level.

5.4 Limitations of the Study

Various challenges were encountered in this research including data limitations from the NSE and inadequate empirical evidence from emerging markets.

The aim of the study was to investigate the clustering pattern observed at the NSE for all the quoted stocks. Among the data required for the study was the price for the highest limit order bid and lowest limit order ask of a given stock on a particular trading day. This would require a full day’s data on the trading activity of a stock to be available for the period under study. However, the NSE indicated that they only maintain records for opening and closing prices. Due to this limitation, it was assumed that the opening price is the lowest limit order-ask while the closing price is the highest limit order-bid.

There was also inexistent empirical evidence of research on price clustering in emerging markets including Africa. Much of the studies around price clustering have concentrated on developed markets and in particular the USA stock markets, the London Stock Exchange, the Dutch stock markets and Asian Pacific markets. The fact that stock markets of developing countries are said to exhibit the weak form efficiency against the strong efficiency for similar markets in developed countries mean that not all the hypotheses that have been formulated to explain price clustering in the developed markets can predict the same behaviour in developing countries like Kenya.

5.5 Recommendations for Implementation

The study finds that there is a tendency of prices to cluster around certain numbers as evidenced by the 67.88 percent of numbers clustering around the digit 5 and that price clustering is positively related to the number of trades. It is thus recommended that if firms are to increase the number of trades of their shares they should consider pricing their shares according to the preferences of investors who prefer shares or stocks whose prices end with 5 or 0.

5.6 Recommendations for Further Study

The factors examined in this study looked at the microstructure of the firms as the variables examined in the study were only related to the firm's internal structure. Further areas of study on price clustering should examine the macroeconomic factors such as interest rates, foreign exchange rates and Gross Domestic product of the economy as this is also likely to affect the pricing of the stocks.

REFERENCES

Aitken, M., Brown, P., Buckland, C., Izan, H., & Walter, T. (1996). Price clustering on the Australian Stock Exchange. *Pacific-Basin Finance Journal*(4), 297-314.

Aşçıoğlu, A., Comerton-Forde, C., & McInish, T. H. (2007). Price Clustering on the Tokyo Stock Exchange. *The Financial Review*(42), 289-301.

Ball, C. A., Torus, W. A., & Tschoegl, A. E. (1985). The degree of price resolution: The case of the gold market. *Journal of Future Markets*(5), 29-43.

Bollen, N., Smith, T., & Whaley, R. E. (2003). Optimal contract design: For whom? *Journal of Futures Markets*(23), 719-750.

Brown, P., Chua, A., & Mitchell, J. (2002). The influence of cultural factors on price clustering: evidence from Asia-Pacific stock markets. *Pacific-Basin Finance Journal*(10), 307-332.

Christie, W. G., & Schultz, P. H. (1994). Why do NASDAQ market makers avoid odd-eighth quotes. *Journal of Finance*(49), 1813-1840.

Christie, W. G., Harris, J. H., & Schultz, P. H. (1994). Why did NASDAQ market makers stop avoiding odd-eighth quotes. *Journal of Finance*(49), 1841-1860.

Chung, K. H., Kim, K. A., & Kitsabunnarat, P. (2005). Liquidity and quote clustering in a market with multiple tick sizes. *Journal of Financial Research*(28), 177-195.

De Ceuster, M. J., Dhaene, G., & Schatteman, T. (1998). The hypothesis of psychological barriers in stock markets and Benford's Law. *Journal of Empirical Finance, 5*(4), 263-279.

De Grauwe, P., & Decupere, D. (1992). Psychological barriers in the foreign exchange market. *Journal of International and Comparative Economics, 1,* 87-101.

Dickinson, J. P., & Muragu, K. (1994). Market Efficiency in Developing Countries: A Case Study of the Nairobi Stock Exchange. *Journal of Business Finance and Accounting, 21*(1), 133-149.

Easley, D., & O'Hara, M. (1987, September). Price, Trade Size, and Information in Securities Markets. *Journal of Financial Economics, 19*(1), 69 - 90. doi:10.1016/0304-405X(87)90029-8

Goodhart, C., & Curcio, R. (1991). The clustering of bid-ask prices and the spread in the foreign exchange market. *London Schoool of Economics*(Discussion Paper 110).

Greener, S. (2008). *Business Research Methods.* Dr. Sue Greener & Ventus Publishing ApS. Retrieved from http://www.ftvs.cuni.cz/hendl/metodologie/introduction-to-research-methods.pdf

Grossman, S. J., Miller, M. H., Cone, K. R., Fischel, D. R., & Ross, D. J. (1997). Clustering and competition in asset markets. *Journal of Law and Economics*(40), 23-60.

Gwilym, O. A., Clare, & Thomas, S. (1998). Extreme price clustering in the London equity futures and options markets. *Journal of Banking and Finance*(22), 1193-1206.

Hameed, A., & Terry, E. (1998). The effect of tick size on price clustering and trading volume. *Journal of Business Finance and Accounting*(25), 849-867.

Harris, L. (1991). Stock price clustering and discreteness. *Review of Financial Studies*(4), 389-415.

Hornik, J., Cherian, J., & Zakay, D. (1994). The influence of prototypic values on the validity of studies using time estimates. *Journal of the Market Research Society, 36*(2), 145-147.

Huang, R. D., & Stoll, H. R. (2001). Tick Size, Bid-Ask Spreads, and Market Structure. *The Journal of Financial and Quantitative Analysis*(36 (4)), 503-522.

Kahn, C., Pennachi, G., & Sopranzetti, B. (1999). Bank deposit rate clustering: Theory and empirical evidence. *Journal of Finance*(54), 2185-2214.

Ley, E. (1996). On the peculiar distribution of the U.S. stock indexes' digits. *The American Statistician, 50*(4), 311-313.

Liu, H.-C., & Witte, M. D. (2013). Price Clustering in the U.S. Dollar/Taiwan Dollar Swap Market. *The Financial Review*(48), 77–96.

Loomes, G. (1988). Different experimental procedures for obtaining valuations of risky actions: Implications for utility theory. *Theory and Decision, 25*(1), 1-23.

Mitchell, J. (2001). Clustering and Psychological Barriers: The Importance of Numbers. *The Journal of Futures Markets*(21), 395–428.

Niederhoffer, V. (1965). Clustering of stock prices. *Operations Research*(13), 258-265.

Niederhoffer, V. (1966). A new look at clustering of stock prices. *Journal of Business*(39), 309-313.

Niederhoffer, V., & Osborne, M. F. (1966). Market making and reversal on the stock exchange. *Journal of the American Statistical Association*(61), 897-916.

Ohta, W. (2006). An analysis of intraday patterns in price clustering on the Tokyo Stock Exchange. *Journal of Banking and Finance*(30), 1023-1039.

Osborne, M. F. (1962). Periodic structure in the Brownian motion of stock prices. *Operations Research*(10), 345-379.

Palmon, O., Smith, B. A., & Sopranzetti, B. J. (2004). Clustering in real estate prices: determinants and consequences. *The Journal of Real Estate Research, 26*(2), 115-136.

Parkinson, J. M. (1987). The EMH and the CAPM on the Nairobi Stock Exchange. *East African Economic Review, 3*(2), 105-110.

Preece, D. A. (1981). Distribution of the final digits in data. *The Statistician, 30*(1), 31-60.

Schelling, T. C. (1960). *The Strategy of Conflict.* Cambridge Massachusetts: Harvard University Press.

Schwartz, A., Van Ness, B. F., & Ness, R. A. (2004). Clustering in the futures market: Evidence from S&P 500 futures contracts. *Journal of Futures Markets*(24), 413-428.

Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics, 69*, 99-118.

Sonnemams, J. (2003). *Price clustering and natural resistance points in the Dutch Stock Market: A natural experiment.* Discussion Paper, University of Amsterdam.

Sopranzetti, B. J., & Datar, V. (2002). Price clustering in foreign exchange spot markets. *Journal of Financial Markets*(5), 411-417.

Thaler, R. (1992). *The winners' curse: paradoxes and anomalies of recent life. In: A Russell Sage Foundation Book.* New York: Maxwell Macmillan International.

Timarr. (2010, February 24). *Irrational Numbers: Price Clustering & Stop Losses*. Retrieved from The Psy-Fi Blog: http://www.psyfitec.com/2010/02/irrational-numbers-price-clustering.html

Vogt, Bodo, Uphaus, A., & Albers, W. (2001). Numerical Decision Processing Causing Stock Price Clustering? *Homo-economicus*(18 (2)), 1-12.

Yule, G. U. (1927). On reading a scale. *Journal of the Royal Statistical Society, 90*(3), 570-579.

APPENDICES

Appendix I: Companies Listed on the NSE between January 2009 and December 2013

AGRICULTURAL
Eaagads Ltd
Kakuzi Ltd
Kapchorua Tea Co. Ltd
The Limuru Tea Co. Ltd
Rea Vipingo Plantations Ltd
Sasini Ltd
Williamson Tea Kenya Ltd

AUTOMOBILES & ACCESSORIES
Car & General (K) Ltd
CMC Holdings Ltd
Marshalls (E.A.) Ltd
Sameer Africa Ltd

BANKING
Barclays Bank of Kenya Ltd
CFC Stanbic of Kenya Holdings Ltd
Diamond Trust Bank Kenya Ltd
Equity Bank Ltd
Housing Finance Co. Kenya Ltd
I&M Holdings Ltd
Kenya Commercial Bank Ltd
National Bank of Kenya Ltd
NIC Bank Ltd
Standard Chartered Bank Kenya Ltd
The Co-operative Bank of Kenya Ltd

COMMERCIAL AND SERVICES
Express Kenya Ltd
Hutchings Biemer Ltd
Kenya Airways Ltd
Longhorn Kenya Ltd
Nation Media Group Ltd
Scangroup Ltd
Standard Group Ltd
TPS Eastern Africa Ltd
Uchumi Supermarket Ltd

TELECOMMUNICATION & TECHNOLOGY
Safaricom Ltd

CONSTRUCTION & ALLIED
ARM Cement Ltd
Bamburi Cement Ltd
Crown Paints Kenya Ltd
E.A.Cables Ltd
E.A.Portland Cement Co. Ltd

ENERGY & PETROLEUM
KenGen Co. Ltd
KenolKobil Ltd
Kenya Power & Lighting Co Ltd
Total Kenya Ltd
Umeme Ltd

INSURANCE
British-American Investments Co.(Kenya) Ltd
CIC Insurance Group Ltd
Jubilee Holdings Ltd
Kenya Re Insurance Corporation Ltd
Liberty Kenya Holdings Ltd
Pan Africa Insurance Holdings Ltd

INVESTMENT
Centum Investment Co Ltd
Olympia Capital Holdings Ltd
Trans-Century Ltd

MANUFACTURING & ALLIED
A.Baumann & Co Ltd
B.O.C Kenya Ltd
British American Tobacco Kenya Ltd
Carbacid Investments Ltd
East African Breweries Ltd
Eveready East Africa Ltd
Kenya Orchards Ltd
Mumias Sugar Co. Ltd
Unga Group Ltd

GROWTH ENTERPRISE MARKET SEGMENT (GEMS)
Home Afrika Ltd

Source: Nairobi Securities Exchange, 2009 – 2013