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AN EMPIRICAL STUDY OF PRICE CLUSTERING ON THE NAIROBI SECURITIES EXCHANGE

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Abstract

Purpose: The purpose of this study was to empirically investigate price clustering phenomenon on the Nairobi Securities Exchange for the period 2009 to 2013.

Materials and methods: The study used secondary sources of data obtained from the Nairobi Securities exchange. The study revealed that there has been a preference by investors for stock whose prices end with the digit 5 and this accounted for 67.88 percent of all the stocks examined and 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 behavior a multivariate regression model used by Harris (1991) was adopted where price clustering was regressed against stock volatility, number of trades, market capitalization, and own stock price.

Results: The regression results indicated that the number of trades as well as Market Capitalization was positive and significantly related to price clustering. The study also found the stock price 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 number of trades, stock volatility, own stock price and the market capitalization. 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 number 5 and that price clustering is positively related to number of trades

Recommendations: 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 ends with 5 or 0.

Keywords: *Price clustering, stock volatility, securities exchange*

1.0 INTRODUCTION

1.1Price 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, et al. (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 (1985) finds a similar clustering in the London gold market, as do Goodhart and 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 (2004) and bank deposit rates (Kahn, 1999).

Clustering is a numbers anomaly associated with investors' irrational behavior. 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.

1.1.1 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, 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 behavioral 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, 1994).

1.1.2 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 below:

(i)	Below Kshs. 20	Kshs. 0.05
(ii)	Kshs. 20 -50	Kshs. 0.25
(iii)	Kshs. 51 -100	Kshs. 0.50
(iv)	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 (1996) and Aşçıoğlu (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 and Muragu (1994) reject the applicability of

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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 of 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 paper aims to empirically investigate price clustering at the Nairobi Securities Exchange. The following research question forms the subject of this study:
Does clustering of stock prices exist at the Nairobi Securities Exchange?

1.3 Research Objective

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

2.0 LITERATURE REVIEW

2.1 Price Clustering Hypotheses

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.

2.1.1 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 (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.

2.1.2 The Negotiation Hypothesis

Extending from the price resolution hypothesis, Harris (1991) advances the negotiation hypothesis, arguing that clustering should be considered when analyzing 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.

2.1.3 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.

2.1.4 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.

2.1.5 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 not worthy 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.

2.1.6 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).

2.1.7 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 (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.

2.2 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 behavioral 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

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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 and 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.

2.3 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 and 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 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.

3.0 RESEARCH METHODOLOGY

This study adopted a descriptive design in order to obtain more information about clustering. The study aimed to establish the degree of price clustering at the Nairobi Securities Exchange, determine the measures of price clustering, define the explanatory variables, and indicate their expected relationship to the degree of price clustering that is observed. The population encompassed observations from all the 61 stocks that were listed at the Nairobi Securities Exchange (NSE) for the period 2009-2013. From this dataset, a separate database was constructed comprising observations on the ordinary fully paid shares of the 61 listed companies that traded at least three times per day, on average, during the period under study.

Only regular trades transacted in the five and half hours of Normal Trading Mode were considered in this paper. 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.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.

4.0 DATA ANALYSIS AND PRESENTATION OF FINDINGS

4.1 Descriptive Statistics

The table 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 the table 1 it can also be observed that shares whose prices ended with five’s were most preferred given that it appeared 38,441. On the other hand the least preferred share price was those ending with three as they only appeared 1,733 times.

The table 1 also indicates that 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 was 1.425. The stock volatility which was computed from the average price of the share prices had a mean of 8.256 and with a standard deviation of 11.07 over the same period.

The market capitalization for the NSE quoted firms over this 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 trades of shares in average was approximately 37 and the number of trades on average deviated by approximately 76.

Table 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

The table2 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 the there is a high preference for shares trading for 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 2 below was share prices which ended with the number three.

Table 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

4.2 Trend Analysis

This section presents the general behavior of the study variables over the period of study. The trends of stock volatility, market capitalization, stock prices, number of trades as well as the price clustering is also presented.

4.2.1 Price Clustering

Figure 1 Price Clustering of Stocks 2009-2013

An analysis of price clustering for the stocks quoted on the NSE indicated that investors have preference for shares whose price ends with digit five as indicated in the figure 1 below. The table 2 above indicated that 67.88 percent of all stock prices (38,441 trades) have five and 4.55percent of all stock prices have (2,576 trades) have zero as the last digit. This shows that 72.43 percent of all observations show a digit of 0 or 5 as the last digit.

4.2.2 Turnover and Price Clustering Trend Analysis

The figure 2 below shows the turnover and price clustering movements for the period of study, 2009-2013. It can be concluded that the turnover and price clustering of stock for the companies

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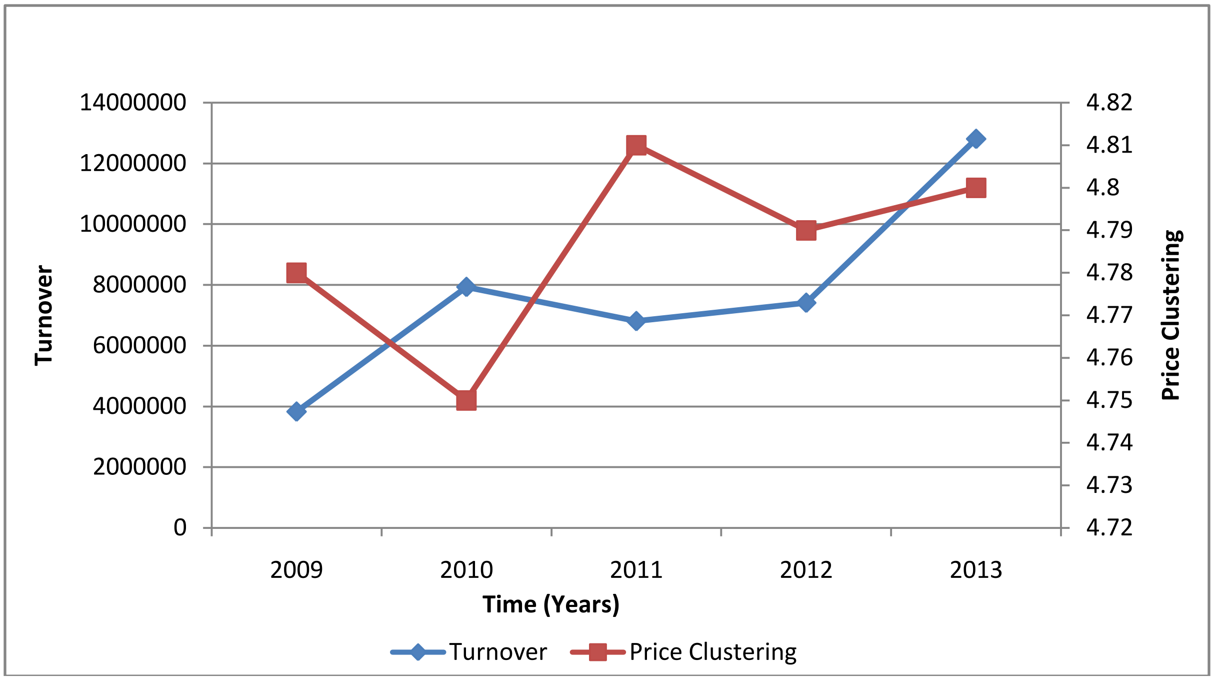
listed on the NSE moving in the same direction (i.e. there stock turnover has been increasing over time so has been the price clustering of the same stocks).

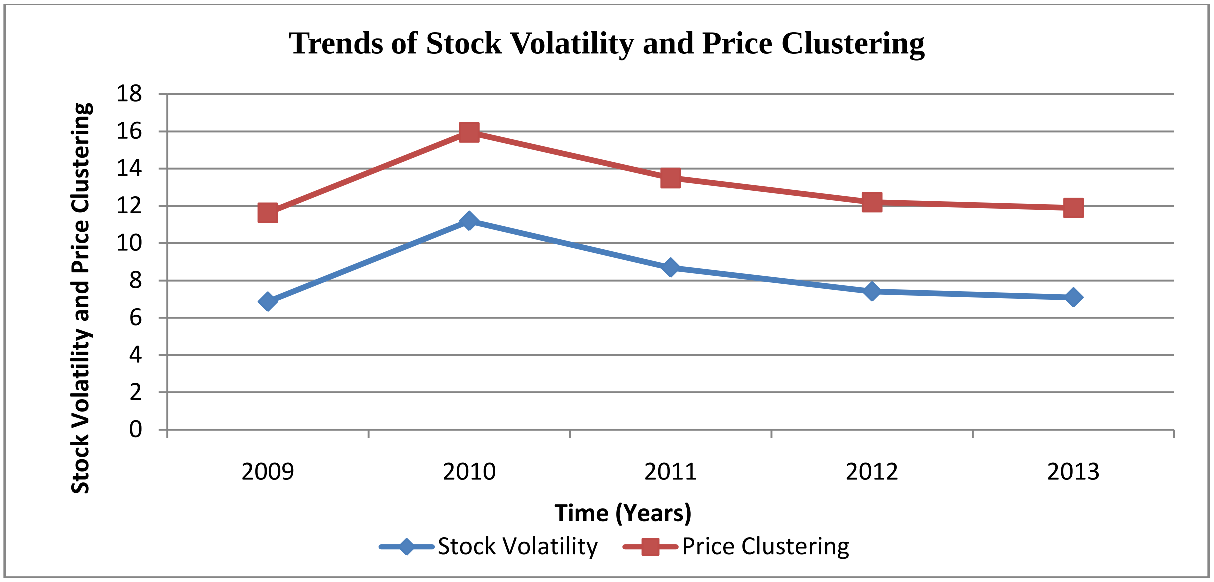
Figure 2 Turnover and Price Clustering Trend Analysis 2009-2013



4.2.3 Stock Volatility and Price Clustering Trend Analysis

The figure 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 the stock volatility and price clustering has 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 declined as exhibited in the figure 3 below. This was also the case with price clustering. It thus can be concluded that the stock volatility has been moving in the same direction with price clustering.

Figure3 Stock Volatility and Price Clustering Trend Analysis 2009-2013



4.2.3 No. of Trades and Price Clustering Trend Analysis

The figure 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 that as the frequency of trading increases the observed price clustering behavior diminishes.

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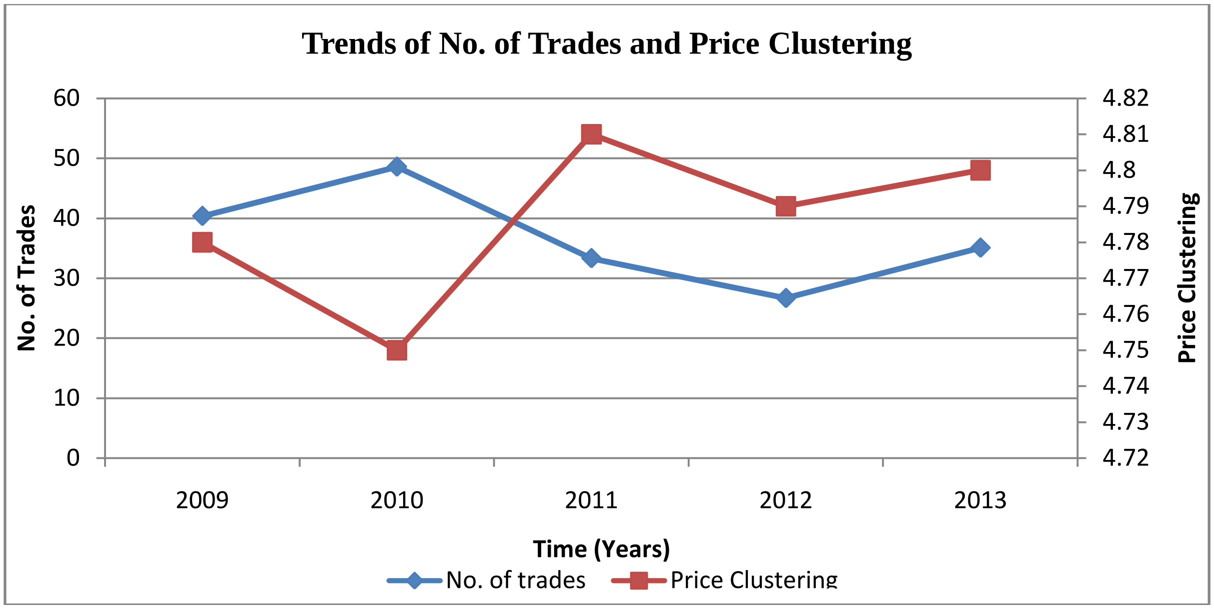
Figure 4 No. of Trades and Price Clustering Trend Analysis 2009-2013



4.3 Correlation Matrix

The table 3 below shows the correlation matrix of Clustering Price, no. of trades (Deals), Turnover, and Stock Volatility. The correlation matrix shows that the 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 the clustering reduces. As indicated by the frequency of the last digit of stock prices the 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 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). 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 3 Correlation Matrix 2009-2013

	Clustering	Price	Deals	Turnover	Stock Volatility
Clustering	1.0000				

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

p-Values indicated in brackets

4.4 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 are 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 co linearity problem. The table 4 below presents the Tolerance and VIF values, the VIF values as indicated by the table indicates 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 Test for Multicollinearity

	Co linearity 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

4.5 Regression Results

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

4.5.1 Model Summary Results

The table 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 5 Model Summary

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

4.5.2 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. The 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 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			

4.5.3 Multivariate Regression Model Results

A multivariate regression was conducted where price clustering was regressed against No. of Trades (Deals), Market Capitalization, Stock Volatility, and Price and the results are presented in table 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 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 that it exhibited 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 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 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

5.0 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Findings.

The study findings indicate that the stocks whose prices end with digit 5 are most preferred (38,441 observations) accounting for 67.88 percent of price clustering 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.

5.2 Conclusions

The study results showed that price clustering is evident in the NSE as revealed by the frequency of the appearance of the last digit of the stock prices. Most stock prices were cluster 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 who also found out stock prices to be clustered around some number. This is in line with the findings of Niederhoffer (1965) who also documented clustering of limit orders which were taken from the order book of a specialist on the NYSE. This finding 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 also found out 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.

5.3 Recommendations

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 number 5 and that price clustering is positively related to 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 ends with 5 or 0.

5.4 Suggested Areas 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 the interest rates, foreign exchange rates and Gross Domestic product of the economy as this is also likely to affect the pricing of the stocks.

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