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Inferring Market Expectations from Stock Prices at the Nairobi Securities Exchange

Warutumo Johnson Wachira
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School of Finance and Applied Economics
Strathmore University
Nairobi, Kenya

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Warutumo Johnson Wachira

Signature ....

Date ....4th DECEMBER 2015..........

This Research Project has been submitted for examination with my approval as the Supervisor.

Okoth Ferdinand Othieno

Signature ....

Date ....4/12/2015..........

School of Finance and Applied Economics

Strathmore University

Abstract

This study assesses market expectations by analysing the relationship between NSE 20 index returns, dividend growth and the Kenyan Treasury bill rate. Univariate and multivariate time series analysis is employed to examine the relationship. The study finds that there is no long run relationship between the index and dividends using the Johansen Cointegration test. The Vector Auto Regressive model shows that most lagged values of returns are significant in explaining movements in the index returns and past movements of the NSE 20 returns are important in inferring the future movements in the index/stock prices. Unidirectional causality from the dividend growth to the weekly returns was found which shows that movements in the dividend growth appear to lead those of the returns of the NSE 20 index. Fundamentals guide returns, but with a lag of more than seven periods. In weekly analysis, investors are driven by dividend growth after seven periods, which is the average time (in weeks) it takes between dividend announcement and dividend payout. In the monthly analysis, previous four months data is found to be useful in inferring future movements of the index especially during period of shocks. Relating this findings to the Campbell Shiller stock price decomposition, stock prices in the NSE are mainly determined by future expectations of excess returns. The study expects market expectations to be effected on the stock price, seven weeks after dividends are announced. The movements in the prices depends on the magnitude and sign of the dividend change.

Key words: returns, dividend growth, market expectations.

List of Abbreviations

ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
AR	Auto Regression
CAPM	Capital Asset Pricing Model
CBK	Central Bank of Kenya
CCAPM	Consumption Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
HQIC	Hannan-Quinn Information Criterion
LR	Likelihood Ratio
MA	Moving Average
NSE	Nairobi Securities Exchange
PACF	Partial Auto Correlation Function
SCIC	Schwarz Information Criteria
VAR	Vector Auto Regression
VECM	Vector Error Correction Model

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1. Introduction

1.1. Background to the study

As first posited by scholars such as Fisher (1930), the price of a share should equal the present value of its future dividends. This analogy assumes that market participants are fully rational, and that there is no mispricing. However, Shiller (1981) finds that share prices are highly volatile to be determined by fundamentals. In addition, Vuolteenaho (2002) confirms market inefficiency by showing that stock markets are macro inefficient. This mispricing in the market is evident as a result of misvaluations generated from decision biases (Hirshleifer, 2001).

Another shortcoming of discounting cash flows is that it requires forecasting of inputs such as expected future cash flows or dividend. Due to uncertainty, forecasting the future accurately is a challenge. Hence, a second way of dealing with the measurement of the present value of dividends or cash flows is to reverse engineer the future cash flows that justify the current market price. This is one way of quantifying expectations in the market, assuming that prices in the market are determined only by its fundamentals.

Since market prices are not purely determined by fundamentals, a pricing framework is required, that most accurately determines the prices of stocks in the market and/or its movements. Researchers such as Campbell and Shiller (1988), Campbell (1991), Campbell and Ammer (1993) decompose the stock price into expectations of future real dividend growth and expectations of future excess returns, which are justified to determine stock price movements in the market. Campbell (1990) notes that the log linear approximation is surprisingly accurate. Kleidon (1986) finds that the log linear models utilized are better than nonlinear models. Analysing expectations of future real dividend growth and expectations of future excess returns accounts for both fundamentals and market expectations, which are considered to determine asset prices.

The expectations quantification approach has the advantage in that forecasting is not necessary thus available data of prices and dividends can be used, then by working backwards, market expectations can be inferred and assessed. Stock price movements could signify a revision in the expectations (Balke & Wohar, 2006) and changes in expectations can be assessed for reasonableness. Realizing extreme market expectations enables investors to make informed decisions that will probably gain return. An example of realizing gains by observing the markets and inferring information on market expectations, is the concept of momentum in stock prices. Jagadeesh and Titman (2011) show that momentum portfolios have significant profits when compared to other portfolios based on models such as the Fama French three factor model. Momentum (Jagadeesh & Titman, 1993) implies that stocks that perform the best over the past three to twelve month period tend to continue and outperform worse stocks in the next three to twelve month period.

1.2. Motivation of the study

Stock prices are realized through investors' activities in the stock market. Investors choose prices based on fundamentals and their expectations of fundamentals and excess returns. Such activity can be driven by rational changes in expectations due to news about future dividends and news about future returns (Campbell, 1990). Irrational market prices are evidence of 'false' extreme expectations arising from misvaluations (Hirshleifer, 2001), uncertainty (Pastor & Veronesi, 2009), speculative trading, all by which an investor can take advantage. Campbell and Kyle (1993) notice overreactions in the market whereas Edwards (1968) and Barberis et al (1998) notice underreactions as other possible signs of mispricing. All in all, expectations, whether rational or irrational, determine market pricing.

Quantifying these expectations in the market relieves an investor of the challenge of forecasting. The model to be justified has the advantage of using available data to infer important information and hence make informed investment decisions. This way investors only have to assess market expectations and determine their appropriate investment action.

1.3. Problem Statement

Rational asset prices are defined as a present value of discounted expected future dividends. This rational price can be understood as an idealization, a sort of equilibrium. It is the price predicted by the net present value relationship if investors have perfect foresight about future dividends. However, investors' expectations about future dividends are usually not fulfilled. This is as a result of the frequent mispricing in the market. The present value framework is faced by challenges such as market volatility anomaly and difficulty in accurate forecasts. In addition, behavioral aspects of the market are not considered in assuming presence of rational prices.

It is important to consider market expectations in assessing stock prices since the market drives stock prices. An investor will invest in a stock because he/she expects the price to go up (expectation of future excess returns) and/or dividends to increase (expectation of future real dividend growth). The study aims to quantify and analyze market expectations. Identifying extreme expectations provides an opportunity to gain.

1.4. Research Objectives

To develop a justifiable method of analysing expectations from stock prices in the Kenyan stock market.

1.5. Research Questions

1. Is there a pricing framework that justifies the market price accurately?

2. Can we work backwards, given the market price and any other set of data available, to infer expectations from the market price in Kenya?

1.6. Scope of the study

The focus of this research is the Nairobi Securities Exchange. The NSE 20 index is used as a proxy for the aggregate stock price, due to availability of data and absence of illiquidity issues[1]. Additional risk premiums is demanded for holding illiquid stocks, and this can result in anomalies such as risk mispricing (Shefrin & Statman, 1994). Other effects such as small firm effect (Blanz, 1981) and the ignored firm effect (Arbel and

[1] This is due to the specification of the NSE 20 constituent stocks. They are selected based on a weighted market performance during the period under review based on the following criteria among others: trading activity measures i.e. market capitalization, shares traded, deals/liquidity and turnover during the period under review. *(Review of NSE 20 Share Index Press Release)*

Strebel, 1981) are potentially avoided by selecting the NSE 20 index which constitutes fairly large cap and liquid stocks in Kenya.

Monthly and weekly data on the index, dividends accruing to the NSE 20 constituent companies, and the Kenyan Treasury Bill rates will be collected from 2005 to 2014, a ten year period. Analysis on different time horizons will be compared, that is, monthly and weekly. To justify this, Fama (1963, 1965) found small predictability in stock returns in the short term, not enough to cover for trading costs. However, high frequency trading in modern markets today decreases transaction costs by reducing bid ask spreads as trading volumes increase (Gerig & Michayluk, 2010). Furthermore, momentum strategies imply predictability in the short term. Using monthly and weekly data helps in analysing the short time horizons and comparing the use and accuracy of expectations inferred from each.

1.7. Justification of the study

Investors need to understand asset prices and how they are formed, to make good economic decisions. A summary of the research of 2013 Nobel laureates, Eugene Fama, Peter Hansen and Robert Shiller, points to the fact that prices guide economic decisions. Mispricing may result to crises. As a result, empirical asset pricing helps promote understanding of asset prices.

Markets determine stocks prices, through expectations on the stocks. It is clear that although fundamentals play a role in determination of asset prices, market mechanism also play a role, if not bigger. Developments in asset pricing research is showing shifts from the Efficient Markets Hypothesis to behavioral finance. Market anomalies have facilitated this shift. Thus, behavioral factors are of concern in understanding asset prices. Andrew Lo (2004) lists some of the departures from EMH.[2]

[2] These include loss aversion (Kahneman and Tversky, 1979 and Shefrin and Statman, 1985), overconfidence (Fischoff and Slovic, 1980), miscalibration of probabilities (Lichtenstein et al., 1981), regret (Bell, 1982), psychological accounting (Kahneman and Tversky, 1981), overreaction (DeBondt and Thaler, 1986), hyperbolic discounting rate (Laibson, 1997), and herding (Huberman and Regev, 2001) (Andrew Lo, 2004). They are arranged in chronological order, although the list of EMH departures is not exhausted.

Shiller, the pioneer of behavioral finance, carried out surveys to understand investor behavior. Shiller (1990) recognizes price feedback models in the market, as a form of difference equations where prices are formed based on previous stock price movements, and thus expectations that they might continue in the same trend. Through interaction, the market participants drive this further. This helps explain bubbles in stock markets.

Shiller states that EMH has 'gross oversimplifications'. Goetzmann and Massa (1999) show that feedback traders who follow trends encourage momentum whereas smart traders move the other way and cause reversals (Bondt & Thaler, 1985). Shefrin and Statman link Bayesian principles to decision making. They identify noise traders and information traders, with the latter trading using Bayesian principles in updating their beliefs in a timely manner. In addition, David Hirshleifer (2001) recognizes contrarian trading and active trading as behavioral factors showing departures from EMH. All the above shows the significance of behavioral finance.

2. Literature Review

The literature review focuses on understanding stock prices, the stock market and pricing models developed, with a focus on the Campbell Shiller stock price decomposition that is influential in analysing market expectations in this study.

2.1. Predictability of Stock Prices

2.1.1. Short Term Predictability

Fama (1963, 1965) uses tests and finds little predictability, small to cover trading costs. However, in modern markets, Gerig and Michayluk (2010) show that high frequency trading decreases transaction costs as traders trade more. Lizernberger et al. (2012) show that technology has helped reduce bid ask spreads. This leads to a realization that in the short term, predictability of asset prices could be profitable.

French and Roll (1986) and Lo and MacKinlay (1988) also find small predictability in stock returns. There was stronger autocorrelation for smaller, less frequently traded stocks. Lehmann (1990) shows that large trades lead to short term pressure on stock prices.

2.1.1.1 Random Walk

The random walk hypothesis originates from Bachelier (1900) and was formalized by Mandelbrot (1963) and Samuelson (1965) (Understanding Asset Prices, 2013). It implies that forecast errors should be unpredictable. If they are predictable, then the model is incorrectly specified. It was empirically studied by Fama (1963, 1965) and Fama and Blume (1966) who find little predictability, thus a confirmation of the random walk hypothesis. Developments in asset pricing theory led to price to price feedback models, which was criticized based on the random walk hypothesis. Shiller (1990) shows a term representing other factors that affect demand other than the price, which can show random walk in stock prices. Random walk hypothesis argues that past prices are of very little use. This could not be true. Pastor and Veronesi (2009) show that investors are uncertain about parameters and they learn by observing data. Individual trading depend on past performance.

2.1.1.2. Event Studies

Event studies show that information is incorporated very swiftly in asset prices. Hilda Rono (2013) finds that stock returns in the Nairobi Securities Exchange are significant on the second month after announcement, implying informational efficiency during such events. Roll (1984) finds markets have informational inefficiency, due to sizeable differences between spreads estimated from daily and weekly data. Informational inefficiency could be present in other periods other than during significant events.

Fama et al. (1969) study price reactions to stock splits and confirm that information is quickly incorporated. They find abnormal returns after the announcement. This implies that stock prices do not generally follow fundamentals.

2.1.2. Long term predictability

Studies show that predictable patterns could be due to risk and its compensation. There is significant economic predictability in stock prices in the long term. Fama and Schwert (1977) suggest that short term interest rates could be used to forecast stock market returns. Fama and French (1988a) find predictability increases with the time horizon.

2.1.3. Predictability factors

Fama and French (1988a) find that the dividend price ratio can explain variations in excess returns. Campbell and Shiller (1988b) show that the dividend price ratio can be explained by variation in expected dividends and discount rates, and that it is positively affected by future dividend growth. The dividend price ratio is promoted by researchers such as Campbell (1991) to be a powerful predictor. Basu (1977, 1983) finds that high dividend price ratio stocks outperform stock with low dividend price ratios.

Fama (1990) identifies three sources of variation in stock returns: shocks to expected cash flows, variation through time in the discount rate that price expected cash flows and shocks to discount rates. They are believed to help judge on the rationality or efficiency of stock prices. He finds 58% to be explained by the three sources, a possibility to presence of irrational stock prices. This confirms that prices are mainly formed by market expectations.

Campbell and Shiller (1988a) find that the long moving average of real earnings helps predict future returns. Consistent with Fisher (1980), earnings could be a better figure than dividends to predict returns in the very long term. In the relatively short term, irrationality in the market lead to prices that do not follow fundamentals.

2.1.4. Cross Section

Models such as the CAPM (Sharpe, 1964, Lintner, 1965, and Mossin, 1966) and the Fama French three factor model (Fama and French, 1993) show the cross section of asset returns. The value of a particular stock depends on its expected cash flows and the discount factor. Its discount factor is affected by risk premium of the stock and time preferences. A shortcoming of both models is that it assumes the market portfolio. Corhart (1991) suggests adding momentum as a fourth factor, to help capture more of the mispricing and investor irrationality.

2.2. Stock Market

2.2.1. Efficient Market Hypothesis

EMH states that prices follow martingales. Fama (2011) argues that prices are sub martingales in that they fully reflect all available information, and according to the random walk, price changes are independently and identically distributed. EMH proposes that individuals form expectations rationally, markets aggregate information efficiently, and equilibrium prices incorporate all available information (Lo, 2004). EMH is criticized by researchers, which leads to emergence of behavioral finance, pioneered by Robert Shiller.

Fama (2011) defends EMH by proposing a joint hypothesis problem in the tests that conclude against market efficiency. The joint hypothesis problem is an asset pricing model that specifies equilibrium expected returns and market efficiency. However, Shiller (2003) notices that Fama recognizes the anomalies of market efficiency.

The fundamental of EMH is that risk and return govern pricing. Presence of bubbles and crashes raise questions if whether the EMH still holds.

2.2.2. Behavioural Finance

Studies on the discount factor used in discounting future cash flows lead to realizations that the discount factor observed in data shows investors are not fully rational. Shiller (1981) argued of fads in the market. He confirms this in carrying out surveys with John Pound (Pound and Shiller, 1989).

Shiller (2003) notices that Fama in a 1970 article recognizes of anomalies like slight serial dependencies in stock market returns. Shiller (1981) shows the volatility anomaly in stock markets. He demonstrated that stock prices move much more than explained by dividend streams. Shiller utilized three discount rates to show the excess volatility of stock prices using data in the US stock market from around 1880 to around 2000.

EMH proposes that the variance of the price must be smaller than the variance of the realized discounted value of future dividends. The stock price should equal the expected value of the actual subsequent dividends accruing to the share, $P_{i,t} = E_t(P^*_{i,t})$. Incorporating an error, $P^*_{i,t} \equiv P_{i,t} + u_{i,t}$. Shiller implies that the variance of the price must be smaller than the variance of the realized discounted value of future dividends, $Var(P^*_{i,t}) \equiv Var(P_{i,t}) + Var(P^*_{i,t} - P_{i,t})$. Since variance cannot be negative, $Var(P^*_{i,t}) > Var(P_{i,t})$. A constant discount factor was assumed. The findings were that the price variance was much larger than the variance of the discounted sum of future dividends. Subsequent tests by West (1988) confirm the volatility anomaly. Leroy and Porter (1981) also find evidence of excess volatility with a different methodology. They construct a joint test of price volatility and payoff volatility from a bivariate model for dividends and prices. Campbell and Shiller (1988) handle non-stationarity issues using a VAR model including price dividend ratio and change in log dividends.

Developments in behavioural finance lead to models such as price to price feedback theory. If the feedback is not interrupted, a bubble arises that is unrelated to fundamentals. This can account for the crashes in the market. The feedback models are a form of difference equations (Shiller, 2003). Its advantage is that it shows that most investors are preconditioned by past experiences and have systemic biases. Kahneman and Tversky (1974) show that investors seek closest match to past patterns. The behavioural capital asset pricing model developed by Shefrin and Statman (1994) recognise interaction of noise traders and information traders. They recognise that risk is not priced the right way, shifting the efficient frontier. Noise trader steer the market away from price efficiency. To confirm market irrationality, Shiller (2003) suggests that smart traders may tend to amplify the effect of feedback traders.

Shiller concludes by stating that the fundamental value of stocks is hard to measure, and that market prices do not necessarily follow fundamentals. Underpriced stocks will not necessarily go up, as indicated by valuations.

Adaptive Market Hypothesis tries to reconcile EMH and behavioral finance. Andrew Lo (2004) applies evolutionary principles to financial markets. He states that humans generally satisfice and do not optimize. Prices reflect as much information as dictated by environmental conditions and nature of market participants. Analysing market expectations is a quantitative approach to such developments.

2.2.3. Market Volatility and Efficiency

Market prices have been established to move too much to be explained by fundamentals. Additionally, the market does not have perfect foresight on future dividends and returns. To quantify this, Shiller (2003) show that if investors had perfect foresight, the volatility of prices should be equal to the volatility of future subsequent dividends accruing to the shares. Market volatility is also confirmed in other markets. Shiller finds that the volatility of long term interest rates is greater than the volatility of short term interest rates. Ideally, it should be vice versa, since the long term interest rates are a weighted average of future short term interest rates. Excess volatility in markets can imply predictability.

Markets are also found to be macro inefficient and macro efficient, by Vuolteenaho (2002) and Paul Samuelson (2009). Vuolteenaho (2002) used VAR to show that book to market value explains much of the future firm's earnings. The price to dividend ratio is confirmed as a good forecast of long term future changes in future dividends (Jung and Shiller, 2002).

2.3. Pricing Models

2.3.1. Discounted Cash Flow

Assuming no arbitrage in the market, Ross (1978) and Harrison and Kreps (1979) find a pricing equation. The no arbitrage pricing formula is $P_{i,t} = E_t(m_{t+1}x_{i,t+1})$, where m is the discount factor and x the return on the asset. This is consistent with the discounted cash flow method that states that the price of an asset should be equal to the discounted value of its future cash flows.

2.3.2. The Discount Factor

The discount factor, m is studied and leads to development of models such as the consumption CAPM by Merton (1973), Lucas (1978) and Breeden (1979). The Generalized Method of Moments developed by Hansen to test dynamic asset pricing models, rejects the CCAPM.[3] Shiller (2003) recognizes that no certain discount factor can explain the price series.

2.3.3. Behavioural models

The behavioral models considered are the behavioral capital asset pricing model (Shefrin and Statman, 1994), feedback models (Shiller, 1990, DeLong et al, 1990b, Cutler et al, 1990) and the stock price decomposition (Campbell and Shiller, 1988, 1989, Campbell, 1991, Campbell and Ammer, 1993).

The behavioral capital asset pricing model proposes a single driver property that differentiates inefficient from efficient markets. Noise traders introduce a second driver that steers the market away from efficiency. Price efficiency protects noise traders, and inefficiency makes noise traders codominant. The effect of noise traders is recognized in stock markets.

[3] Hansen's GMM allows estimation of nonlinear systems and estimating dynamic economic models using panel data. Hansen and Singleton (1982) also tested the CCAPM and found that the CCAPM did not fit the data very well. CCAPM implied too low a volatility of the stochastic discount factor.

Feedback models recognize that investors buy into trends (DeLong et al, 1990b). Cutler et al (1990) show that feedback traders take advantage of the time lag in fundamental traders seeking signals of the asset's payoff. Shiller (1990) develops a feedback model in which the demand for a speculative asset equals the distributed lag of prices plus other factors that affect demand. The model was criticized of serial correlation in stock prices, against the random walk hypothesis. He notes that the last term can show the random walk in asset prices. The feedback models help explain crashes and bubbles.

The Campbell Shiller price decomposition employ a log linear approximation of stock returns. They establish a linear relationship between the log price dividend ratio and expectations of future dividends and excess returns. They find that expectations of future excess returns is more significant in explaining volatility in stock returns.

2.4. Theoretical Underpinning of the study: The Campbell Shiller price decomposition

Campbell and Shiller (1988) provide the stock price decomposition using annual observations and nominal data. The nominal series is deflated using a consumer price index. The real price is P_t and real dividend is $D_{t,}$ both at time t. The realized logarithm of the gross return is,

$$h_{1t} \equiv log((P_{t+1} + D_t)/P_t) = log(P_{t+1} + D_t) - log(P_t) \qquad (1)$$

Over *i* periods, the return is given by $h_{it} = \sum_{j=0}^{i-1} h_{1,t+j}$.

2.4.1. The derivation of the stock price decomposition

The relationship between realized log one period return, the dividend growth rate and log dividend price ratio is given by,

$$h_{1t} = \log(\exp(\delta_t - \delta_{t-1}) + \exp(\delta_t)) + \Delta d_t \qquad \textbf{(2)}$$

The above equation is derived from Campbell and Shiller (1987) where the Gordon growth model[4] is considered. This is in a static world. The linear relationship between log return, log dividends and log prices is h_t approximated by,

$$\xi_t = k + \rho \log(P_{t+1}) + (1-\rho)\log(D_t) - \log(P_t) \qquad \textbf{(3)}$$

where k is a constant and ρ is a number less than 1 but close to 1. Campbell (1991) points that having ρ closer to 1 makes sense since it implies an increase in stock returns expected in the distant future is more associated with a smaller drop in today's price than stock returns expected in the near future i.e. the factor that is more observable by the market.

Comparing equation (3) with equation (1), the differences $\rho\Delta\log(P_{t+1}) + (1-\rho)\Delta\log(D_t)$ approximates $\Delta\log(P_{t+1} + D_t)$. It is derived from breaking down $\Delta\log(P_{t+1} + D_t)$.

$$\Delta\log(P_{t+1} + D_t) \simeq \frac{P_{t+1}+D_t-P_t-D_{t-1}}{P_t+D_{t-1}} = \frac{P_{t+1}-P_t}{P_t+D_{t-1}} + \frac{D_t-D_{t-1}}{P_t+D_{t-1}} \qquad \textbf{(4)}$$

Assuming the ratio is of price to price plus dividends is approximately constant at level ρ, we get $P_t = \rho(P_t + D_{t-1})$ and $D_{t-1} = (1-\rho)(P_t + D_{t-1})$. Equation (4) becomes,

$$\Delta\log(P_{t+1} + D_t) \simeq \frac{\rho(P_{t+1}-P_t)}{P_t} + \frac{(1-\rho)(D_t-D_{t-1})}{D_{t-1}} = \rho\Delta\log(P_{t+1}) + (1-\rho)\Delta\log(D_t) \quad \textbf{(5)}$$

Referring to the Gordon growth model, if h_t as h and Δd_t as g are constant then, $P_t/P_t + D_{t-1}$ is also constant. Thus $P_t/P_t + D_{t-1} = \exp(g-h) = \rho$.[5]

The constant k in equation (3) allows it to hold for levels in the static world. In a static world, $\delta_t = \delta = \log(1/\rho - 1)$.[6]

The constant k is defined as $k = -\log(\rho) - (1-\rho)\delta$, to make $\xi = h$,

$$\xi = (1-\rho)(d_t - p_{t+1}) + (p_{t+1} - p_t) + k$$

[4] D/P=h-g, where h is the constant return and g is the constant dividend growth.
[5] $\exp(g) = D_t/D_{t-1}$ and $\exp(h) = P_t + D_{t-1}/P_{t-1}$, thus $\exp(g-h) = \Delta d_t - h_t = P_t/P_t + D_{t-1} = \rho$
[6] $\rho = P_t/(P_t + D_{t-1})$ so $1/\rho - 1 = P_t + D_{t-1} - P_t/P_t$, which is equals to $D_{t-1}/P_t = \delta_t$.

$$\xi = (1-\rho)\delta + g - \log(\rho) - (1-\rho)\delta = g - \log(\rho) = h^7 \quad \textbf{(6)}$$

The above does not hold if the market is not static. A first order Taylor series expansion of $h_t = \log(P_{t+1} + D_t) - \log(P_t)$ makes it hold. The expansion still leads to the same equation $\xi = h$. Errors in neglecting higher orders is small and almost constant, as explained by Campbell and Shiller.

From a first order Taylor expansion around $\delta_t = \delta_{t+1} = \delta$ and $\Delta d_t = g$ gives

$$h_t = k + \rho p_{t+1} + (1-\rho)d_t - p_t$$

$$h_t = k + \delta_t - \rho\delta_{t+1} + \Delta d_t \quad \textbf{(7)}$$

Solving forward with a condition that $\lim_{i\to\infty} \rho^i\, \delta_{t+i} = 0$ (that it does not explode as i increases) gives,

$$\delta_t \simeq \sum_{j=0}^{\infty} \rho^j (h_{t+j} - \Delta d_{t+j}) - \frac{k}{1-\rho} \quad \textbf{(8)}$$

The log dividend price ratio is written as discounted value of all future returns h_{t+j} and dividend growth ratesΔd_{t+j}, discounted at a constant rate ρ less a constant$\frac{k}{1-\rho}$.

Turning into an economic model, a dynamic Gordon model is developed. Suppose a theory with an ex post discount rate $E_t h_t = E_t r_t + c$, assuming we can observe the ex post discount rate r_t. The expected real return on a stock is the expected real return on commercial paper plus a constant. The ex post real return on commercial paper can be used as the ex post discount rate. Substituting in r_{t+j}, we get,

$$\delta_t \simeq E \sum_{j=0}^{\infty} \rho^j (r_{t+j} - \Delta d_{t+j}) + \frac{c-k}{1-\rho} \quad \textbf{(9)}$$

where $r_{t+j} - \Delta d_{t+j}$ is the growth adjusted discount rate. It is linear in logs, an advantage pointed out by Kleidon (1986).

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[7] Remember $\rho = \exp(g - h)$, so $h = g - \log(\rho)$.

The result is that δ granger causes real dividend growth, and that expectations of future discount rates drive stock prices. This recognizes the power of the log price to dividend ratio.

Going back to equation (2) $h_{1t} = \log(\exp(\delta_t - \delta_{t-1}) + \exp(\delta_t)) + \Delta d_t$, d/p is assumed to follow a stationary stochastic process. The constant expected returns model is rejected again, by analysing multiperiod returns. h_t can be approximated by ξ_t, linear in $\delta_t, \delta_{t+1} and\ \Delta d_t$;

$$\xi = \delta_t - \rho\delta_{t+1} + \Delta d_t + k \qquad \mathbf{(10)}$$

The multiperiod return is $\xi_{it} = \sum_{j=0}^{i-1} \rho^j \xi_{i,t+j}$. The summation has a well-defined limit. Assuming that dividends paid are reinvested in an asset that pays a fixed real rate of return,

$$H_{it} = \ln\{\exp(\delta_t - \delta_{t+i} + \sum_{j=0}^{i-1} \Delta d_{t+j}) + \sum_{j=0}^{i-1} \exp(\delta_t + \sum\nolimits_{k=0}^{j} \Delta d_{t+k} + r(i-j-1)\}\mathbf{(11)}$$

The first term in brackets is P_{t+i}/P_t, and the other term is the terminal value of total dividends from time period t to t+i-1. This is consistent with basic principles; that the return on a stock is through its capital gains and dividends received.

2.4.2. Summary of the price decomposition

Campbell (1991) states that stock prices are as a result of changing expectations of future dividends and future returns. Taking a first order Taylor approximation of the equation relating log stock returns to log stock prices and dividends and solving forward imposing a terminal condition (that log dividend price ratio does not follow an explosive process), gives a relation of unexpected stock return in period t+1 to changes in expectations of future dividend growth and future stock returns,

$$h_{t+1} - E_t h_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j h_{t+1+j} \qquad (12)$$

E_t is the expectation formed at the end of period t. If the LHS is negative, then either expected future dividend growth is lower or expected future stock return must be higher or both. ρ is justified to be less than 1 but close to 1. Campbell and Shiller derive their ρ from sample means. They set $\rho = 0.9962$ for monthly data, and $\rho = (0.9962)^3$ for quarterly data. Their results are not sensitive to variation in ρ within a plausible range (Campbell, 1991).

Having $v_{h,t+1} = h_{t+1} - E_t h_{t+1}$ and $\eta_{d,t+1}$ and $\eta_{h,t+1}$ representing the first and second term in the above equation respectively, the equation can be represented by $v_{h,t+1} = \eta_{d,t+1} - \eta_{h,t+1}$.

2.4.3. Econometric and empirical analysis

2.4.3.1. Univariate time series approach

Campbell (1991) starts with assuming that expected stock return follows a univariate autoregressive process of order one. The innovation in the one period ahead stock return is, $\mu_{h,t+1} = (E_{t+1} - E_t)h_{t+2}$. If the expected returns follows an univariate time series process, $\eta_{h,t+1}$ is an exact function of μ_{t+1}. Campbell states the AR(1) as, $E_{t+1}h_{t+2} = \phi E_t h_t + \mu_{t+1}$, hence $\eta_{h,t+1} = \frac{\rho\mu_{t+1}}{1-\rho\phi}$. The univariate approach is found to hardly give any definite results in estimating autocorrelations.

Campbell (1991) proposes an alternative in analysing excess stock return. Excess return is defined as $e_{t+1} \equiv h_{t+1} - r_{t+1}$, with r_{t+1} as the short term interest rate. Combining with equation (6),

$$e_{t+1} - E_t e_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j r_{t+1+j}$$
$$- (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j e_{t+1+j} \quad \textbf{(13)}$$

Thus $v_{h,t+1} = \eta_{d,t+1} - \eta_{r,t+1} - \eta_{e,t+1}$.

2.4.3.2. VAR framework

Campbell (1991) proposes an alternative to the univariate time series approach. The univariate approach is found to delivers weak evidence against white noise returns, that all autocorrelations are zero. It loses power by forecasting returns using only past returns ignoring informational variables. The VAR can calculate the impact an innovation in expected return will have on the stock price (Campbell, 1991). He recognizes Kandel and Stambaugh (1988) on showing that a low order VAR can account for 'several long run characteristics of data'.

Starting with real stock return, Campbell defines a vector z_{t+1} with k elements, the first one being h_{t+1}. The vector follows a first order VAR, $z_{t+1} = Az_t + w_{t+1}$. A vector with the first element as 1 picks out h_{t+1} from z_{t+1}, $h_{t+1} = e1'z_{t+1}$ and $v_{t+1} = e1'w_{t+1}$. The first order generates multi period forecasts of future returns,

$$E_t h_{t+1+j} = e1'^{A^{j+1}z_t} \qquad \textbf{(14)}$$

The discounted sum of revision in the forecasted returns can be written as,

$$\eta_{h,t+1} \equiv (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j h_{t+1+j} = e1' \sum_{j=0}^{\infty} \rho^j A^j w_{t+1} = e1'\rho A(1-\rho A)^{-1} w_{t+1}$$
$$= \lambda' w_{t+1} \qquad \textbf{(15)}$$

This implies that $\eta_{d,t+1} = (e1' + \lambda')w_{t+1}$. Campbell notes that the variance of unexpected stock returns can be decomposed into the variance of news about cash flows, and variance of news about future expected returns and a covariance term.

The second subsequent analysis is on excess returns. A vector z_{t+1} has excess returns, e_{t+1} and real interest rates, r_{t+1} as its second element. A vector *e2* has one as its first and second element, and singles out excess returns and real interest rates from z_{t+1}.

Campbell obtains news about future excess returns as $\eta_{e,t+1} = \lambda' w_{t+1}$, and news about real interest rates as $\eta_{r,t+1} = \mu' w_{t+1}$.[8] The residual news about future dividends is given by $\eta_{d,t+1} = (e1' + \lambda' + \mu) w_{t+1}$.

2.5. Summary: Market Expectations

Shiller (1990) notes the 'gross' oversimplification in the Efficient Market Hypothesis. He finds that popular models differ across markets, and what is common is investor psychology. Expectations formed by the market show the investor psychology. Quantifying and analysing expectations is important in understanding formation and movements of asset prices. The Campbell Shiller decomposition provides a method of quantifying expectations. It states that the stock price is determined by expectations of future real dividend growth and expectations of future excess returns.

A dynamic Gordon model, which is linear in logs, is developed from the Gordon growth model that is in a static world. It is an economic model of the dividend price ratio, and has economic reasons and backing. A VAR framework that allows non-stationary dividends and prices is employed (Campbell and Shiller, 1988). The log dividend price ratio is found to Granger cause real dividend growth, and that expectations of future discount rates drive stock prices. Campbell and Shiller (1988b) decompose returns and linearize it around the log dividend price ratio and the log dividend growth.

Subsequently, Campbell (1991) states that stock price changes are as a result of changing expectations of both future dividends and future returns. Returns are forecasted by considering informational variables, a multivariate approach that has more power than the univariate models, for example, feedback models. The univariate models does not fit data very well. The stock price decomposition developed, provides a method to quantify expectations. Using available data, market expectations can be inferred and analyzed.

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[8] $\eta_{r,t+1} = e2'(1 - \rho A)^{-1} w_{t+1} = \mu' w_{t+1}$

2.5.1. Identified research gap

Asset pricing models in behavioral finance, have been developed. Barberis and Shleifer (2000) propose style investing to explain price movements. Shefrin and Statman (1994) develop a behavioral capital asset pricing model. The Campbell Shiller price decomposition is the most convincing. It is consistent with the reasoning that fundamentals and the market are the factors determining asset prices and asset price movements. The Campbell Shiller decomposition of stock prices states that prices are determined by expectations of future real dividend growth and future excess returns. In this way, the model relates stock prices, stock returns and dividends (Campbell, 1991). Stock returns are regressed onto variables known in advance. The time evolution of the forecasting variables is studied. This results into a VAR. Campbell (1991) points out that forecasting returns by considering informational variables increases its power.

The method used by this paper focuses on inferring market expectations instead of forecasting. This introduces a new paradigm of the possibility of expectation quantification. However, according to Shiller (1981), popular models differ across markets. The study will focus on an individual market, the Kenyan stock market. Once the market expectations are inferred, they can be assessed for extreme measures.

Investors learn by observing data and subsequent learning (Pastor & Veronesi, 2009). Prior beliefs are revised after receiving new information. Trading is influenced by, and depends on past performance. *Prior actual events* and *current circumstances* can be used to assess market expectations. In assessing current circumstances, Baker and Wurglar (2007) develop a sentiment index highly correlated with aggregate stock returns and Jagadeesh and Titman (2011) relate the state of the economy to momentum profits, and find that low market volatility implies optimism.

Assessing market expectations implies that valuation and a 'correct' discount factor is not necessary. Shiller (2002) points out the need of someone finding the definition of discount rates that produces a present value series that 'fits' the actual price better than his methods in 1989. Various models have not come up with such a discounting factor. Secondly, this study can also help in correctly predicting asset bubbles, which are speculative. Markets do and can crash. This can be in the form of bubbles, demonstrating frailty of some facets of human emotion.

3. Methodology

3.1. Summary

The study aims to infer the expectations of future real dividend growth and expectations of future excess returns from the market. The Campbell Shiller decomposition provides a way of doing the above. The study will initially run a vector autoregressive model of three variables that include returns, dividends, and yields, to determine which variables significantly determine stock price movements in the Nairobi Securities Exchange. Monthly and weekly data will be used to analyze the short term.

The study will collect data on share prices, dividends and rates/yields. Both weekly and monthly data will be collected. The study will involve both sets of data separately to enable comparisons at the end of the study. Variables will be tested on the presence of a unit root to determine specification of the variables e.g. growth or first differences (if variable is I (1)), and also tested for cointegration among variables. Univariate models will be created as preliminary analysis of the three variables.

The study will then perform a Vector Autoregression (or a Vector Error Correction Model if there is cointegration) using past data to determine the dependencies of the variables, and what exactly causes price movements in the NSE i.e. the pricing equation. The number of lags are determined by a multivariate information criteria. The characteristic of the NSE market will be explained using the results obtained from the unrestricted VAR.

3.2. Research Design

This study is exploratory. It determines a pricing equation and whether we can infer expectations from it. Shiller's, Campbell's and Ammer's work influence the study, through their stock price decomposition.

3.3. Population and Sampling

The Nairobi Securities Exchange is used as the stock market under study. The whole population is the stock markets in the world. Each market displays market-specific characteristics.

The NSE 20 index represents the aggregate stock price, due to availability of data and absence of illiquidity issues. Additional risk premiums is demanded for holding illiquid stocks, and this can result in anomalies such as risk mispricing (Shefrin & Statman, 1994). Other effects such as small firm effect (Blanz, 1981) and the ignored firm effect (Arbel and Strebel, 1981) are potentially avoided by selecting the NSE 20 index which constitutes fairly large cap and liquid stocks in Kenya.

The constituent companies of the NSE 20 index over the last ten years are recorded; and the dates of revision of the index when new companies are included in the index to replace removed companies that do not meet existing criteria. The dividends accruing to a share of each of the constituent companies are used only when the company is present in the index.

The 91 day T Bill rate is used since the study looks at the short term; and the 91 day T Bill rate is considered to be the best short term alternative to investments in stocks.

3.4. Nature and Sources of Data

The NSE 20 index is used to represent aggregate market stock price. This is consistent with Shiller's papers that studied the aggregate market. The NSE 20 is made up of the 20 large cap stocks from various industries. Osoro and Ambrose (2013) find that the NSE 20 is still effective, having considered its criticisms of bias by Wahome (2008). The NSE 20 index is collected. The NSE 20 index is collected from myStocks portal, a Nairobi Securities Exchange vendor.

Monthly and weekly data are collected. Dividends is obtained using the dividend accruing to shareholders of companies in the NSE 20 index. All dividend payouts data will be collected from NSE 20 constituent companies' financial reports.

The research will also use the yields of the 91 day T Bill, which will be collected from the Central Bank of Kenya over the last ten years i.e. 2005 to 2014. The time period can be extended depending on future realizations and discoveries when carrying out the study; to get measures like returns which are dependent on the nearest past value.

3.5. Data Analysis and theoretical underpinning of the study

3.5.1. Preliminary Analysis

Campbell and Shiller (1988) provide the stock price decomposition using annual observations and nominal data. This study extends this by using monthly data and weekly data.

The real price is P_t and real dividend is D_t, both at time t. The NSE 20 index is the real price and dividends accruing to shareholders for the constituents of the NSE 20 index during the period is the real dividends. The realized logarithm of the gross return is,

$$h_{1t} \equiv \log((P_{t+1} + D_t)/P_t) = \log(P_{t+1} + D_t) - \log(P_t) \qquad \textbf{(16)}$$

Over *i* periods, the return is given by $h_{it} = \sum_{j=0}^{i-1} h_{1,t+j}$.

Stock excess returns over debt is considered. Excess returns are $h_{it} - r_{it}$, where the interest rate is the 91 day Treasury bill rate.

Stock returns are then regressed on some explanatory variables to determine relationships. R^2 stats are computed to obtain significance level for a Wald test that states that all the coefficients are zero. This corrects for the moving average structure of the error term in multi period returns. Campbell and Shiller point out that a White's test to correct for heteroscedasticity is not necessary, as the results are hardly changed.

This study employs a VAR model to determine the relationships between the variables and their lagged values. Thus, it offers a rich structure by capturing more features of the data. The variables to be used in the VAR are stock price returns, dividends of stocks in the NSE 20 and the Treasury bill rate.

3.5.2. Summary of the Campbell Shiller price decomposition

Campbell (1991) states that stock prices are as a result of changing expectations of future dividends and future returns. Taking a first order Taylor approximation of the equation relating log stock returns to log stock prices and dividends and solving forward imposing a terminal condition (that log dividend price ratio does not follow an explosive process), gives a relation of unexpected stock return in period t+1 to changes in expectations of future dividend growth and future stock returns,

$$h_{t+1} - E_t h_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j h_{t+1+j} \quad \textbf{(17)}$$

E_t is the expectation formed at the end of period t. If the LHS is negative, then either expected future dividend growth is lower or expected future stock return must be higher or both. ρ is justified to be less than 1 but close to 1.

This study considers the variables arising from the stock price decomposition; stock returns, dividend growth and the Treasury Bill rate.

3.5.3. An alternative: Univariate time series

Campbell (1991) starts with assuming that expected stock return follows a univariate autoregressive process of order one. The innovation in the one period ahead stock return is, $\mu_{h,t+1} = (E_{t+1} - E_t)h_{t+2}$. If the expected returns follows an univariate time series process, $\eta_{h,t+1}$ is an exact function of μ_{t+1}. Campbell states the AR(1) as, $E_{t+1}h_{t+2} = \phi E_t h_t + \mu_{t+1}$, hence $\eta_{h,t+1} = \frac{\rho\mu_{t+1}}{1-\rho\phi}$. The univariate approach is found to hardly give any definite results in estimating autocorrelations.

3.5.4. VAR framework

Campbell (1991) proposes an alternative to the univariate time series approach. The univariate time series approach is found to deliver weak evidence against white noise returns, that all autocorrelations are zero. It loses power by forecasting returns using only past returns ignoring informational variables. The VAR can calculate the impact an innovation in expected return will have on the stock price (Campbell, 1991). He recognizes Kandel and Stambaugh (1988) on showing that a low order VAR can account for 'several long run characteristics of data'. Thus, the justification of using a VAR in the study.

3.5.5. Analytical Framework

Wohar and Balke (2006) specify a vector error correction model in the analysis of the Campbell and Shiller price decomposition. They find that the stock decomposition is very sensitive to specification of the VECM (standards level VAR) used. They argue that it is not possible to determine whether expectations of future real dividend growth or future excess returns is responsible for low frequency price movements. They find that movements in the price dividend ratio is persistent. They note that most of the information about low frequency movements in dividend growth and excess returns is contained in the price and not the series of stock prices. This implies a distinction between stock prices and stock price movements. Wohar and Balke's analysis was on US stock data. The study analyses the Nairobi Securities Exchange. The VECM will be used if cointegration among variables is present.

Assumptions made about presence of permanent changes in either real dividend growth or excess returns, affect the stock price decomposition. This paper proposes to analyze historical data in the Nairobi Securities Exchange to determine presence of stationarity in real dividend growth and excess returns. Wohar and Balke suggest that adding more information can help identify the relative significance of real dividend growth and excess stock returns. They propose formally incorporating prior information. This study analyses ten years, a sufficient time period to draw important conclusions on the NSE. An analysis of relative importance could be done by checking the respective coefficient significance from the regression, and granger causality results.

Impulse response functions and variance decompositions give more information about the variables and the Nairobi Securities Exchange.

4. Results, Analysis and Discussions

4.1. Data and Procedure

Weekly and monthly NSE 20 index data was collected. The monthly NSE 20 data spans from January 2001 to July 2015. The weekly data was collected from 3rd January 2003 to 30th October 2015. This was collected from myStocks portal, NSE data vendor. Returns are computed from the index values.

To get dividends, the study took the constituent companies of the NSE 20 index from 2005 to 2014, the period under study. The companies are known from NSE press releases and news articles showing changes in constituents of the NSE 20 index. The index revision dates are collected to ensure that dividends used for the analysis are only the dividends accruing to shareholders of companies in the index at that point of time.

Dividends of the constituent companies were collected over the period under study. The announcement date of the dividends was taken. The dividend accruing to a share in the company changes in the week the new dividend is announced. The dividends of some of the companies are adjusted for stock splits.

The 91 day T Bill rate monthly data was collected from January 2000 to August 2015, sourced from the CBK. Weekly data of the rate was collected from 6th January 1997 to 2nd November 2015.

4.2. Analysis of weekly data

4.2.1. Testing for unit root

Augmented Dickey-Fuller Test	
Null Hypothesis: Variable has a unit root	
Variable	**Prob.**
Weekly Dividends	0.4685
Differenced weekly dividends	0.0000
Dividend Growth	1.2163e-39
Weekly 91 day T Bill Rate	0.0175
NSE 20 Weekly Return	0.0000
*MacKinnon (1996) one-sided p-values.	

Table 1 presents unit root tests for the weekly variables; the weekly dividends, weekly dividend growth, weekly 91 day T Bill rate and the NSE 20 weekly return. A probability that is greater than 5% is stationary i.e. weekly dividends. Dividend growth is used as it is found to be stationary.

Weekly dividends shows a clear positive trend. When testing for stationarity, it is most appropriate to perform the Dickey Fuller test with a trend. The ADF test statistic is greater than the test critical values, therefore we fail to reject the null of a unit root. This does not necessarily confirm that there is a unit root but there is insufficient data to reject the unit root hypothesis. Being interested in the level of integration of the series, dividends are differenced once and then tested for unit root. This time the null hypothesis is rejected at all conventional levels of significance. Differencing makes the data stationary. Another way to make it stationary could be to use dividend growth. The null hypothesis of a unit root in dividend growth is rejected at all conventional levels of significance.

4.2.2. Univariate time series models

Attempting to construct a univariate time series model, the ACF and PACF of the series are plotted. The ACF and PACF for weekly returns show that there is no (if minimal) autocorrelation with weekly returns.

From the above analysis, univariate models can be created for weekly returns. Equation specifications can be opened. Significance of the specific lag identifies the order of the AR or MA model.

Attempting to create univariate models with weekly returns gives low R squared values. For example, an ARMA (2, 3). This equation gives significant coefficients of the second lag of the variable and the second lag of the error term.

The dependent variable is the weekly NSE 20 return		
ARMA (2,3) Maximum Likelihood		
Variable	**Coefficient**	**Prob**
Constant	0.1332 (0.1963)	0.4978
AR (1)	0.0231 (0.1302)	0.8874
AR (2)	0.8705 (0.1658)	0.0000
MA (1)	0.0607 (0.1689)	0.7192
MA (2)	-0.8274 (0.1746)	0.0000
MA (3)	-0.0660 (0.0320)	0.0396
R-squared	0.0162	
Adjusted R-squared	0.0041	

Table 2 shows the results of an ARMA (2, 3) model of weekly NSE 20 returns. The standard errors of the coefficients are in brackets below the coefficients. The probability values, in the third column, show the significance of the variables in the first column. The second lag of weekly returns "AR (2)" and the second lag of the error term "MA (2)" are found to be significant. The explanatory power of the model are shown by the R squared values in the last two rows of the table.

With the NSE 20 index (as it is, a level variable), plotting the autocorrelation functions suggests that the NSE 20 weekly index is an AR (1) index. The model has a high explanatory power.

The dependent variable is the weekly NSE 20 index		
AR (1) Maximum Likelihood		
Variable	**Coefficient**	**Prob**
Constant	4187.5190 (389.4973)	0.0000
AR (1)	1.0040 (0.0250)	0.0000
R-squared	0.9785	
Adjusted R-squared	0.9783	

Table 3 presents the AR (1) model results of the NSE 20 weekly index. The standard errors of the coefficients are in brackets. This model is found to have a much higher explanatory power, with an R Squared of 0.9785.

4.2.3. Johansen Cointegration

The Johansen technique has become the standard means of estimation in time series contexts. The Johansen approach distinguishes stationarity which arises by differencing and by linear combination. Engle Granger did not allow us to do hypothesis tests on the cointegrating relationship itself, but the Johansen approach does. If there exist r cointegrating vectors, only these linear combinations will be stationary. The Johansen approach recognizes both the importance of relationships between the variables included in the system in levels, thereby allowing us to obtain an intimation of the equilibrium relationship between the variables; and the evolution of the system of variables over subsequent time periods hence allowing us to capture the characteristics of the short run dynamics of the system at the same time as estimating a long run equilibrium relationship.

The first step in any cointegration analysis is to ensure that the variables are all non-stationary in their levels. Running a unit root test on the NSE 20 weekly index and the weekly dividend data, both sets of data are found to be non-stationary (I (1) variables); with p-values greater than the conventional levels of confidence.

Augmented Dickey-Fuller Test	
Null Hypothesis: Variable has a unit root	
Variable	**Prob.**
Weekly NSE 20 index	0.7762
Weekly Dividends	0.4685
*MacKinnon (1996) one-sided p-values.	

Table 4 presents the unit root test of the weekly NSE 20 index and weekly dividends. They are both found to be I (1) variables, thus suitable for the Johansen test.

Cointegration Results

Johansen Cointegration Test					
The series is of the weekly NSE 20 index and weekly dividends					
Number of Cointegrating Relationships by the model at 0.05 level					

Data Trend	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Maximum Eigen	0	0	0	0	0
*Critical values based on MacKinnon-Haug-Michelis (1999)					

Table 5 presents the Trace and Max Eigen test on the number of cointegrating relationships between the NSE 20 index and weekly dividends. All data trends and test types show zero cointegrating relationships between the NSE 20 index and weekly dividends.

There is no cointegrating relationship present among the variables (NSE 20 index and weekly dividends) in their levels.

4.2.4. Unrestricted VAR

This is done in order to determine whether there are lead lag relationships for the NSE 20 returns, dividends and the Treasury bill rate. First, we determine the appropriate lag length. The easiest way is to employ a multivariate information criterion.

The Akaike Information Criteria selects 26 lags while the Schwarz criteria selects two lags. A two lag model is parsimonious.

<u>**Model**</u>

The SCIC and the HQIC select **two** lags. Running the VAR gives a model with a relatively low R squared. The second lag of the 91 day T Bill rate is negatively related to weekly returns.

VAR Estimates			
	Weekly Returns	**Weekly Dividend Growth**	**Weekly 91 day T Bill rate**
$Return_{t-1}$	0.0915 (0.0473)	-0.0283 (0.0334)	-0.0024 (0.0050)
$Return_{t-2}$	0.0361 (0.0484)	0.0514 (0.0341)	-0.0057 (0.0051)
$DividendGrowth_{t-1}$	0.1280 (0.0672)	-0.0130 (0.0473)	0.0034 (0.0071)
$DividendGrowth_{t-2}$	0.0261 (0.0677)	-0.0298 (0.0477)	0.0020 (0.0071)
$91dayTBill_{t-1}$	0.0576 (0.3392)	-0.2293 (0.2391)	1.7115 (0.0358)
$91dayTBill_{t-2}$	-0.0606 (0.3405)	0.2797 (0.2400)	-0.7240 (0.0360)
C	0.0248 (0.3211)	-0.2255 (0.2264)	0.0982 (0.0339)
R-squared	0.0203	0.0175	0.9934
Adjusted R-squared	0.0069	0.0040	0.9933

Table 6 presents VAR model estimates. Two lags of each variable compose of the independent variables in each of the three equations. In the weekly returns equation, the lagged returns are found to be significant under 5% confidence level, whereas the lagged variables of returns are found to be significant under 10% confidence level.

Granger Causality

VAR Granger Causality Test	
Null Hypothesis	**Probability**
Dividend Growth does not Granger Cause Weekly Returns	0.1528
Weekly 91 day T Bill rate does not Granger Cause Weekly Returns	0.9822
Both Dividend Growth and 91 day T Bill Rate do not Granger cause Weekly Returns	0.4374
Weekly Returns does not Granger Cause Dividend Growth	0.2598
Weekly 91 day T Bill rate does not Granger Cause Dividend Growth	0.0944
Both Weekly Returns and 91 day T Bill Rate do not Granger cause Dividend Growth	0.1128
Weekly Returns does not Granger Cause Weekly 91 day T Bill rate	0.4358
Dividend Growth does not Granger Cause Weekly 91 day T Bill rate	0.8592
Both Weekly Returns and Dividend Growth do not Granger cause 91 day T Bill Rate	0.7475

Table 7 presents Granger Causality Test of VAR model. We reject the null hypothesis if the probability value is less than the confidence level. Using 10% confidence level, weekly 91 day T Bill rate granger causes dividend growth.

The 91 day T Bill rate is the variable found to granger cause dividend growth; at 10% confidence level.

Dividend growth is found not to granger cause the weekly return of the NSE 20 index, at all confidence levels. There is no evidence of bidirectional causality or feedback mechanisms in weekly data. There is unidirectional causality from the 91 day T Bill rate to the dividend growth. Movements in the 91 day T Bill rate appear to lead those of the weekly dividend growth.

Impulse Response

The study determined impulse response (Appendix page 56). The variables responses to the shocks to other variables are very small except for the response of a variable to its own shock. An effect of a shock to the 91 day T Bill rates on the weekly returns tends to persist. A shock to the dividend growth tends to affect weekly return for approximately 4 periods then it 'cools off'. A shock to returns and dividend growth has minimal effect on the 91 day T Bill weekly rate.

Variance Decomposition

Variance Decomposition of Weekly NSE 20 return			
Period	**Weekly Return**	**Dividend Growth**	**91 Day T Bill rate**
1	100.0000	0.0000	0.0000
2	99.1975	0.7989	0.0036
3	99.1351	0.8611	0.0038
4	99.1346	0.8616	0.0039
5	99.1344	0.8617	0.0039
6	99.1343	0.8617	0.0041
7	99.1341	0.8617	0.0042
8	99.1340	0.8617	0.0043
9	99.1338	0.8617	0.0045
10	99.1337	0.8617	0.0047

Table 8 presents the Variance Decomposition of weekly NSE 20 returns in the VAR model. The values in the second to fourth columns are the proportions in percentages that are affected by the variables in the second row.

Variance Decomposition of Weekly Dividend Growth			
Period	**Weekly Return**	**Dividend Growth**	**91 Day T Bill rate**
1	0.4606	99.5394	0.0000
2	0.6430	99.2400	0.1170
3	1.0885	98.7678	0.1438
4	1.0946	98.7611	0.1443
5	1.0949	98.7573	0.1478
6	1.0949	98.7429	0.1622
7	1.0947	98.7165	0.1888
8	1.0943	98.6801	0.2257
9	1.0938	98.6362	0.2700
10	1.0933	98.5877	0.3190

Table 9 presents a Variance Decomposition of weekly dividend growth in the VAR model. The values in the second to fourth columns are the proportions in percentages that are affected by the variables in the second row.

Variance Decomposition of Weekly 91 day T Bill rate			
Period	**Weekly Return**	**Dividend Growth**	**91 Day T Bill rate**
1	0.2923	0.0761	99.6316
2	0.2043	0.1438	99.6519
3	0.0994	0.2033	99.6972
4	0.0584	0.2324	99.7093
5	0.0463	0.2474	99.7063
6	0.0464	0.2563	99.6973
7	0.0513	0.2621	99.6866
8	0.0578	0.2661	99.6761
9	0.0645	0.2691	99.6665
10	0.0707	0.2712	99.6580

Table 10 presents a Variance Decomposition of weekly 91 day T Bill rate in the VAR model. The values in the second to fourth columns are the proportions in percentages that are affected by the variables in the second row.

A huge proportion in the variation in the returns is caused by its own shocks, as compared to responses to shocks to the other variables. This is the same with the other two variables; in their own variance decomposition.

Variation in returns is wholly caused by its own shocks in the first period. Dividend growth then causes a bigger proportion in returns variation than that caused by shocks to the weekly 91 day T Bill rate.

<u>Alternative Model</u>

The Akaike Information Criterion selects **26** as the optimal lag. Running the VAR gives a model with an R Squared of 0.929852; meaning that the lagged values of the variables explain a huge percentage of the dependent variable. The returns equation has a combine R-squared of 0.926447.

Dividend Growth is found to Granger-cause weekly returns of the NSE 20 index; even at 1% confidence level. The returns and the 91 day T Bill together Granger-cause the dividend growth.

Because dividend growth granger causes returns, an impulse shock on the dividend growth will tend to persist into the future. From a variance decomposition, the proportion in the variation in the returns caused by shocks to dividend growth increases substantially in period 7. This is justified as this is the average period taken between declaration of dividends and payment. The proportion in the variation in the returns is caused by its own shocks reduces as periods pass.

4.3. Analysis of monthly data

4.3.1. Testing for unit root

Augmented Dickey-Fuller Test	
Null Hypothesis: Variable has a unit root	
Variable	**Prob.**
Monthly Dividends	0.3816
Differenced monthly dividends	0.0000
Dividend Growth	0.0000
Weekly 91 day T Bill Rate	0.0218
NSE 20 monthly return	0.0000
*MacKinnon (1996) one-sided p-values	

Table 11 presents unit root test for monthly variables. The probability values are compared to 5% confidence level to fail to reject or reject the null hypothesis of a presence of a unit root. All the other variables except monthly dividends are stationary.

There is a trend in dividends. Carrying out a unit root test with an intercept and a trend shows that dividends is non-stationary. We fail to reject the null hypothesis of a unit root in monthly dividends.

Using first differences of dividends, we reject the null hypothesis of a unit root. Monthly dividends is an I (1) variable. Dividend growth is found to be stationary at all levels of significance. The monthly 91 day T Bill rate is found to be stationary at 5% level of significance. The NSE 20 monthly return is found to be stationary.

4.3.2. Univariate time series models

There is no (if minimal) autocorrelation with weekly returns. Attempting to create univariate models with monthly returns, the research identifies the R squared values. For example, an ARMA (4, 4) has low explanatory power.

The dependent variable is the monthly NSE 20 return		
ARMA Maximum Likelihood		
Variable	**Coefficient**	**Prob**
Constant	0.6472 (0.8301)	0.4372
AR (1)	-0.6394 (0.6581)	0.3334
AR (2)	-0.3324 (0.3291)	0.3148
AR (3)	0.5451 (0.3321)	0.1036
AR (4)	0.2873 (0.5356)	0.5928
MA (1)	0.7392 (0.6632)	0.2675
MA (2)	0.4838 (0.4113)	0.2421
MA (3)	-0.4432 (0.3796)	0.2455
MA (4)	-0.1336 (0.5693)	0.8149
R-squared	0.1006	
Adjusted R-squared	0.0270	

Table 12 present the ARMA (4, 4) model for monthly NSE 20 returns. Values in brackets represent standard errors of the coefficients. The explanatory power is shown by the R squared values in the last two rows of the table.

The study creates an AR (4) model to observe if there are any significant variables.

The dependent variable is the monthly NSE 20 return		
AR (4) Maximum Likelihood		
Variable	**Coefficient**	**Prob**
Constant	0.6365 (0.8335)	0.4467
AR (1)	0.0506 (0.0725)	0.4863
AR (2)	0.0452 (0.0956)	0.6372
AR (3)	0.0720 (0.0895)	0.4227
AR (4)	0.1234 (0.0615)	0.0470
R-squared	0.0305	

Table 13 presents the AR (4) model for the NSE 20 monthly returns. The values in brackets show the standard errors of the coefficients. The fourth lag of NSE 20 returns "AR (4)" is found to be significant. Its probability value (in the third column) is less than 5% confidence level.

The fourth lag's coefficient is significant at 5% level of significance.

4.3.3. Johansen Cointegration

The first step in any cointegration analysis is to ensure that the variables are all non-stationary in their levels. Running a unit root test on the NSE 20 index, dividends and the 91 day T Bill rate; both variables are found to be I (1) variables.

Augmented Dickey-Fuller Test	
Null Hypothesis: Variable has a unit root	
Variable	**Prob.**
Monthly NSE 20 index	0.3789
Monthly Dividends	0.3816
Differenced Monthly NSE 20 index	0.0000
Differenced Monthly Dividends	0.0000
*MacKinnon (1996) one-sided p-values.	

Table 14 presents Unit root tests on monthly NSE 20 index and monthly dividend and also provides a check of the order of the variables. The first differences of the variables (in the sixth and seventh row of the table) are stationary. The probability values are compared to the significance levels to fail to reject or reject the null hypothesis.

Cointegration Results

Johansen Cointegration Test					
The series is of the monthly NSE 20 index and monthly dividends					
Number of Cointegrating Relationships by the model at 0.05 level					
Data Trend	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Maximum Eigen	0	0	0	0	0
*Critical values based on MacKinnon-Haug-Michelis (1999)					

Table 15 presents the cointegrating relationships test between monthly NSE 20 index and monthly dividends. The table summarizes the number of relationships chosen by the two types of test (trace and max Eigen) and by all the six combinations of the data trends and test types.

There is no cointegrating relationship found between the monthly NSE 20 index and monthly dividends accruing to shares of companies composing the NSE 20 index. There is no long run relationship between the two variables.

4.3.4. Unrestricted VAR

This is done in order to determine whether there are lead lag relationships for the NSE 20 returns, dividends and the Treasury bill rate. First, we determine the appropriate lag length. The easiest way is to employ a multivariate information criterion. The sequential modified LR test statistic and the final prediction error choose four lags while the Schwarz Information Criteria choose one lag as the optimal number of lags.

Two information criteria suggest 4 as the optimal number of lags.

VAR Estimates

Standard errors in ( )

	Monthly Returns	**Monthly Dividend Growth**	**Monthly 91 day T Bill rate**
Monthly Return$_{t-1}$	0.0420 (0.0984)	-0.1205 (0.0580)	-0.0037 (0.0152)
Monthly Return$_{t-2}$	0.0116 (0.0996)	0.0713 (0.0586)	-0.0161 (0.0154)
Monthly Return$_{t-3}$	0.0987 (0.0978)	-0.0441 (0.0576)	-0.0126 (0.0151)
Monthly Return$_{t-4}$	0.0453 (0.0987)	0.0654 (0.0581)	-0.0354 (0.0153)
MonthDivGrowth$_{t-1}$	0.0914 (0.1705)	0.0152 (0.1004)	-0.0119 (0.0264)
MonthDivGrowth$_{t-2}$	0.3343 (0.1698)	-0.1738 (0.0995)	-0.0107 (0.0263)
MonthDivGrowth$_{t-3}$	-0.2488 (0.1705)	0.0809 (0.1004)	-0.0929 (0.0264)
MonthDivGrowth$_{t-4}$	0.1293 (0.1629)	-0.0468 (0.0959)	0.0256 (0.0252)
Month91dayTBill$_{t-1}$	-0.3648 (0.5714)	0.3926 (0.3364)	1.4215 (0.0884)
Month91dayTBill$_{t-2}$	0.2611 (0.9444)	-0.1821 (0.5560)	-0.8747 (0.1461)
Month91dayTBill$_{t-3}$	-0.3729 (0.9264)	0.0500 (0.5454)	0.7371 (0.1433)
Month91dayTBill$_{t-4}$	0.6257 (0.5529)	-0.1125 (0.3255)	-0.3636 (0.0855)
C	-0.9717 (1.5080)	-0.6257 (0.8878)	0.7193 (0.2333)
R-squared	0.1176	0.1143	0.9354
Adjusted R-squared	0.0137	0.0101	0.9277

Table 16 presents the VAR model output with four lags according to LR and FPE. The standard errors of the coefficients are in brackets. The coefficients show the absolute change of the variable in the third column of the table when there is a unit change in the variables in the corresponding row of the first column.

Using more lags in the unrestricted VAR increases the explanatory power of the model. A model with 1 lag, as shown in the next page, has a lower R squared value.

Schwarz info criteria chooses one lag. In a model with one lag, the lagged values of the variables are the only significant variables in the respective variables equations.

$$Monthy\ NSE\ 20\ Return_t = 0.1954 + 0.0610\ Return_{t-1} + 0.0612\ MonthlyDivGrowth_{t-1} + 0.0367\ Monthly91DayTBill_{t-1}$$

Granger Causality

VAR Granger Causality Test	
Null Hypothesis	**Probability**
Dividend Growth does not Granger Cause Monthly Returns	0.6902
Weekly 91 day T Bill rate does not Granger Cause Monthly Returns	0.8258
Both Dividend Growth and 91 day T Bill Rate do not Granger cause Monthly Returns	0.8895
Monthly Returns does not Granger Cause Dividend Growth	0.0389
Monthly 91 day T Bill rate does not Granger cause Dividend Growth	0.1015
Both Monthly Returns and 91 day T Bill Rate do not Granger cause Dividend Growth	0.0312
Monthly Returns does not Granger Cause Monthly 91 day T Bill rate	0.1978
Dividend Growth does not Granger cause Monthly 91 day T Bill rate	0.8460
Both Monthly Returns and Dividend Growth do not Granger cause 91 day T Bill Rate	0.4362

Table 17 presents the Granger Causality test between monthly variables. If the probability is less than 5%, we reject the null hypothesis.

All the other variables collectively granger cause dividend growth at 5% significance level. Monthly return granger causes dividend growth. This suggests that managers use monthly data to guide dividend decision making, other than weekly data.

Impulse Response

Effects of shocks to the returns and the dividend growth on returns, tends to slow down after approximately **four periods**. The previous four months data is shown to be useful in guiding returns.

Shocks to the 91 day T Bill rate affects the monthly return, persisting over many periods.

Variance Decomposition

Variance Decomposition of Monthly NSE 20 return			
Period	**Monthly Return**	**Dividend Growth**	**91 Day T Bill rate**
1	100.0000	0.0000	0.0000
2	99.8793	0.1159	0.0048
3	99.8714	0.1163	0.0123
4	99.8646	0.1163	0.0192
5	99.8585	0.1163	0.0253
6	99.8531	0.1163	0.0306
7	99.8484	0.1163	0.0354
8	99.8441	0.1162	0.0396
9	99.8404	0.1162	0.0434
10	99.8371	0.1162	0.0467

Table 18 presents a Variance Decomposition of the monthly NSE 20 return. The values, in percentages, show the proportion explained by shocks to the variables in the second row of the corresponding column.

Variance Decomposition of Monthly Dividend Growth			
Period	**Monthly Return**	**Dividend Growth**	**91 Day T Bill rate**
1	1.7053	98.2947	0.0000
2	5.3008	94.4446	0.2546
3	5.3231	94.2106	0.4663
4	5.3169	94.0331	0.6500
5	5.3118	93.8761	0.8122
6	5.3074	93.7371	0.9555
7	5.3035	93.6143	1.0823
8	5.3000	93.5056	1.1944
9	5.2970	93.4094	1.2937
10	5.2943	93.3242	1.3815

Table 19 presents the variance decomposition of monthly dividend growth. The values, in percentages, show the proportion explained by shocks to the variables in the second row of the corresponding column.

Variance Decomposition of Monthly 91 day T Bill rate			
Period	Monthly Return	Dividend Growth	91 Day T Bill rate
1	0.0248	0.1231	99.8521
2	0.9522	0.0786	98.9692
3	1.3637	0.0693	98.5670
4	1.5660	0.0652	98.3689
5	1.6854	0.0626	98.2520
6	1.7639	0.0610	98.1751
7	1.8190	0.0599	98.1211
8	1.8597	0.0590	98.0813
9	1.8907	0.0584	98.0510
10	1.9149	0.0579	98.0272

Table 20 presents a variance decomposition of the 91 day T Bill monthly rates. The values, in percentages, show the proportion explained by shocks to the variables in the second row of the corresponding column.

The proportion in the variation in the dividend growth caused by shocks to monthly returns increases substantially in period 2. Managers use returns information of the last two months to guide dividend decision making.

4.4. Discussion of results

4.4.1. Weekly Analysis

NSE 20 Return and dividend growth are used as they are stationary. The study creates a univariate model for returns, and found that the lagged value of returns is highly significant to its current value.

Cointegration is not present in the data; meaning there is no long run relationship between the index and dividends. A VAR (using 26 lags) shows that most lagged values of returns are significant in explaining movements in the index returns. This is consistent in that prices hardly follow fundamentals. Shiller (1981) finds that share prices are highly volatile to be determined by fundamentals. Previous values affect the present value of stock prices. It shows that investors follow trends in the index to determine their investment decision and hence guide prices.

Dividend growth granger causes weekly returns of the NSE 20 index. There is unidirectional causality from the dividend growth to the weekly returns. This shows that movements in the dividend growth appear to lead those of the returns of the NSE 20 index.

Fundamentals guide returns, but with a lag of more than seven periods. Variance decomposition of weekly returns suggests the above. Having collected dividends announcement and payments dates of companies in the NSE 20 index, this is the average period it takes for dividends to be paid after they are announced. Hilda Rono (2013) finds that dividends in the Nairobi Securities Exchange are significant, on the second month after announcement, implying informational efficiency during such events. This study, using up to date data, is consistent with the above. Seven periods/weeks translates to about two months.

With weekly data, the market participants of the NSE are largely driven by movement in share prices. Dividends play a role during a certain period; with a lag, after dividends of the constituent companies are announced.

4.4.2. Monthly Analysis

Monthly dividends are non-stationary. Dividend growth, monthly returns and the 91 day T Bill rate are found to be stationary, and are thus used for the study. In a univariate model of the monthly return, the fourth lag of the returns is significant. An AR (1) model is most suitable for the NSE 20 index. The most previous value of the index guides the current value. Adding more lags increases the explanatory power of the univariate model in explaining the index values.

No cointegrating vectors are found among the variables. Two information criteria suggest two lags while the Schwarz Information Criteria chooses one lag as the optimal number of lags. The study finds out that lagged values of returns are the only significant values in the VAR model of monthly returns. Shiller (1990) recognizes price feedback models in the stock market, where prices are formed based on previous stock price movements, and thus expectations that they might continue in the same trend.

Monthly return is found to granger cause monthly dividend growth. This suggests that managers use monthly data (other than weekly data) to guide dividend decision making. A variance decomposition of the dividend growth shows that the effect of a shock to the weekly return increases in the second period/month.

Effects of shocks to the returns and the dividend growth on returns, tends to slow down after approximately four periods. The previous four months data is shown to be useful in guiding returns. This is consistent with the basic points of momentum; momentum strategies imply predictability in the short term. Momentum (Jagadeesh & Titman, 1993) implies that stocks that perform the best over the past three to twelve month period tend to continue and outperform worse stocks in the next three to twelve month period. Shocks to the 91 day T Bill rate affects the monthly return, persisting over many periods.

5. Conclusions and Recommendations

In the short time horizon using weeks as periods, investors are mainly driven by expectation of future stock returns. Increase in the number of lags increases the explanatory power of the VAR model. Looking at the trend in the NSE 20 return helps in knowing the future movement of the return. Investors are driven by dividend growth after c. seven periods, which is the average time (in weeks) it takes between dividend announcement and dividend payout. Hilda Rono (2013) finds that dividends in the Nairobi Securities Exchange are significant, on the second month after announcement, implying informational efficiency during such events. This study, using up to date data, is consistent with the above. Seven periods/weeks translates to about two months.

In the short time horizon using months as periods, investors are also mainly driven by stock returns. Another important finding is that dividend growth is guided by returns, in the second period/month. Effects of shocks to the returns and the dividend growth on monthly returns, tends to slow down after approximately four periods. This shows that the previous four months data is shown to be useful in guiding returns. Investor learn from an average of the last four months.

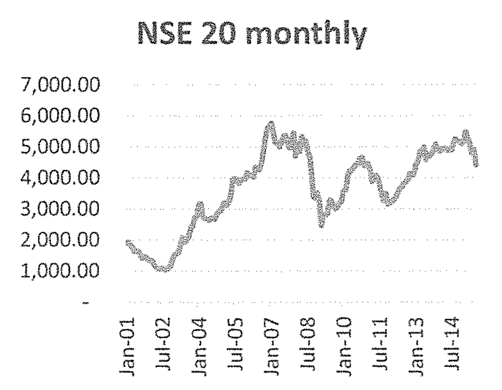
Past movements of the NSE 20 returns are important in inferring the future movements in the index/stock prices. Prices in the Nairobi Securities Exchange are guided by previous prices and hardly by fundamentals or dividends. Dividend growth affects returns after a certain lag. In weekly analysis, investors are driven by dividend growth after c. seven periods, which is the average time (in weeks) it takes between dividend announcement and dividend payout. In the monthly analysis, previous four months data is found to be useful in inferring future movements of the index.

This study outlines mainly the relationships of variables (the returns, dividends and Treasury bill rate) in the Kenyan context, and helps in understanding the characteristics of the Nairobi Securities Exchange and its participants, the market. Market expectations are characterized using results from the analysis of the returns, dividends and the Treasury bill rate over the last ten years.

Investors benefit from knowing how the market has been reacting and how the variables relate to one another. In the near future, investors can gauge the reasonableness of the market by comparing market prices (that are as a result of market action) to the normal characteristics outlined in this study. This study recommends consequent researchers to study on determining excessive market expectations displayed from the market prices. This can help, among other things, identify presence of bubbles in the stock market. Consequent researchers can extend this study to other stock markets.

Appendix

Appendix 1: Graphical display of variables used in the study



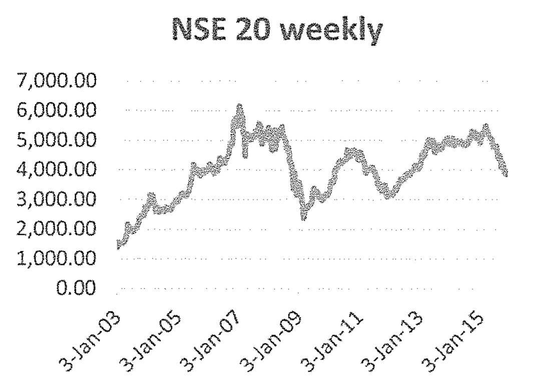
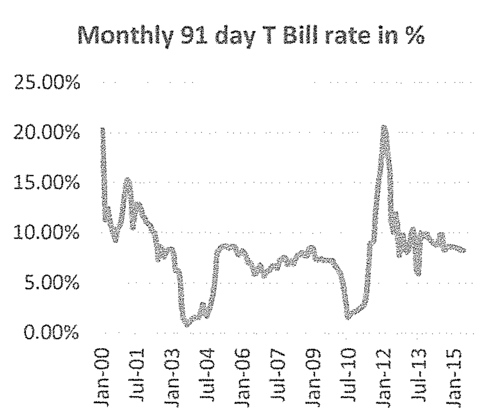


Figure 1 shows the NSE 20 index displayed both monthly and weekly.



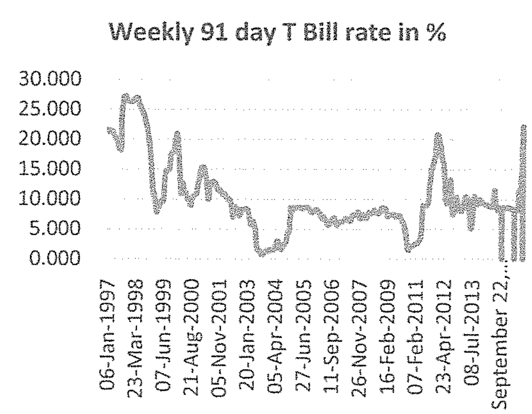


Figure 2 displays the 91 day Kenyan T Bill rate displayed both monthly and weekly.

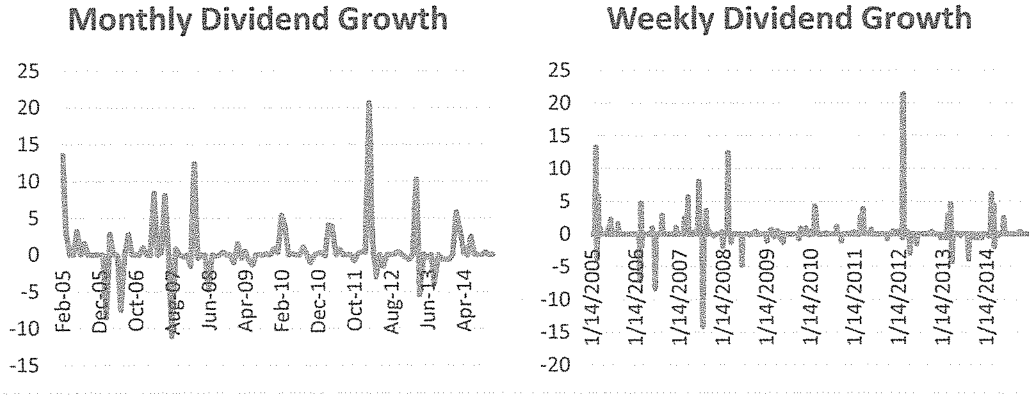


Figure 3 presents the monthly and the weekly dividend growth.

Appendix 2: NSE 20 index constituent companies and dividends from 2004-2014

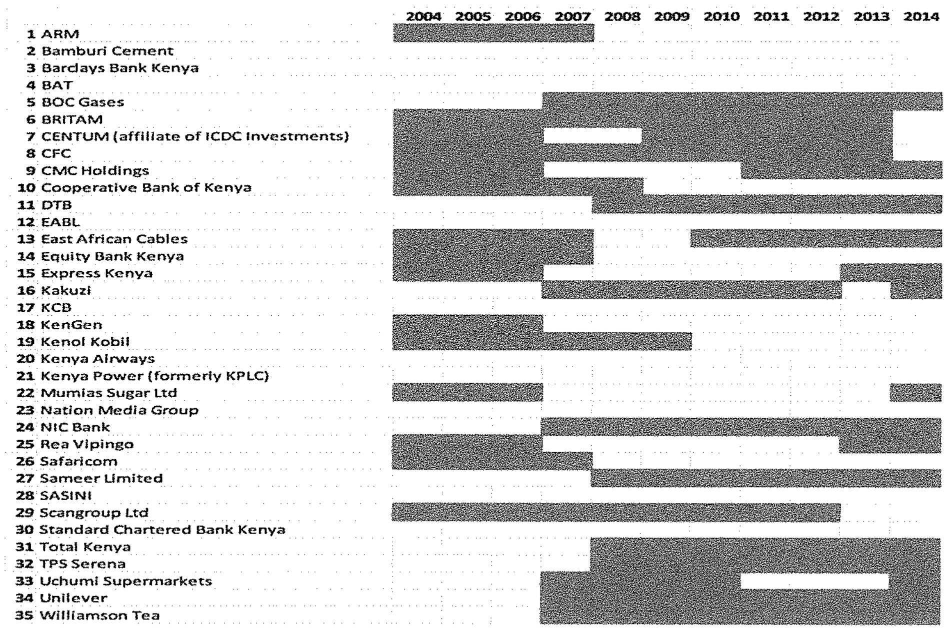


Table 21 presents 4the analytics of the 35 companies that constituted the NSE 20 index from 2004 to 2015. Red shows the period the companies were not present in the NSE 20 index.

Appendix 3: Impulse Response Functions

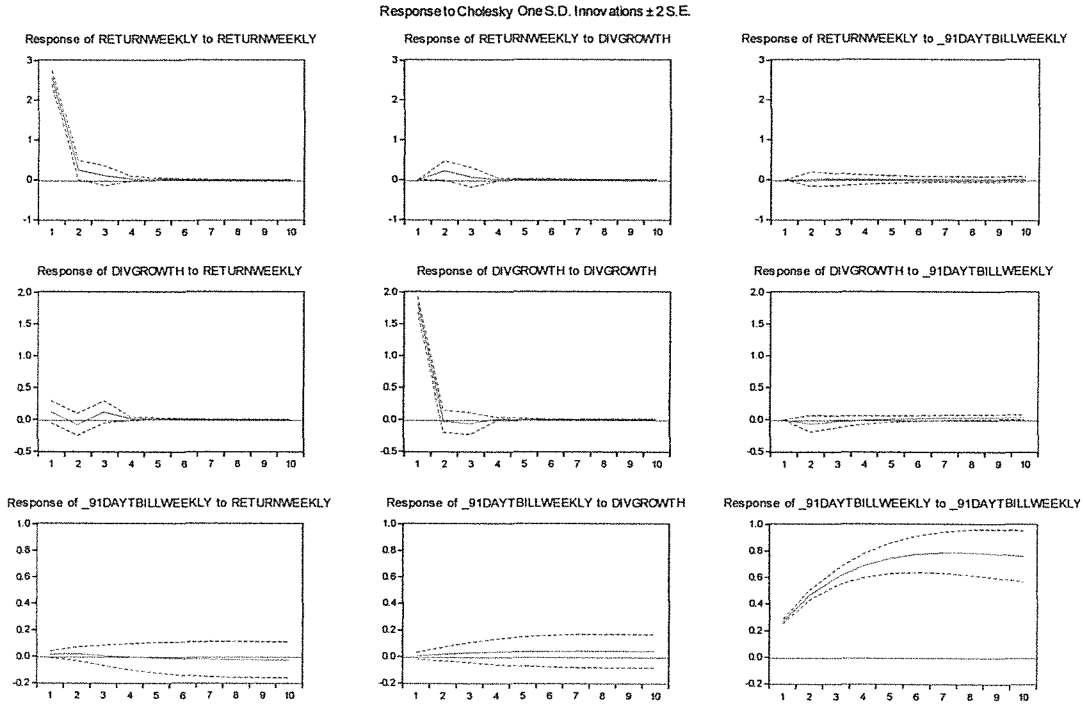


Figure 4: Impulse Response functions of the three variables: NSE 20 weekly returns, weekly dividend growths and the 91 day T Bill weekly rates, for the weekly parsimonious VAR model with two lags.

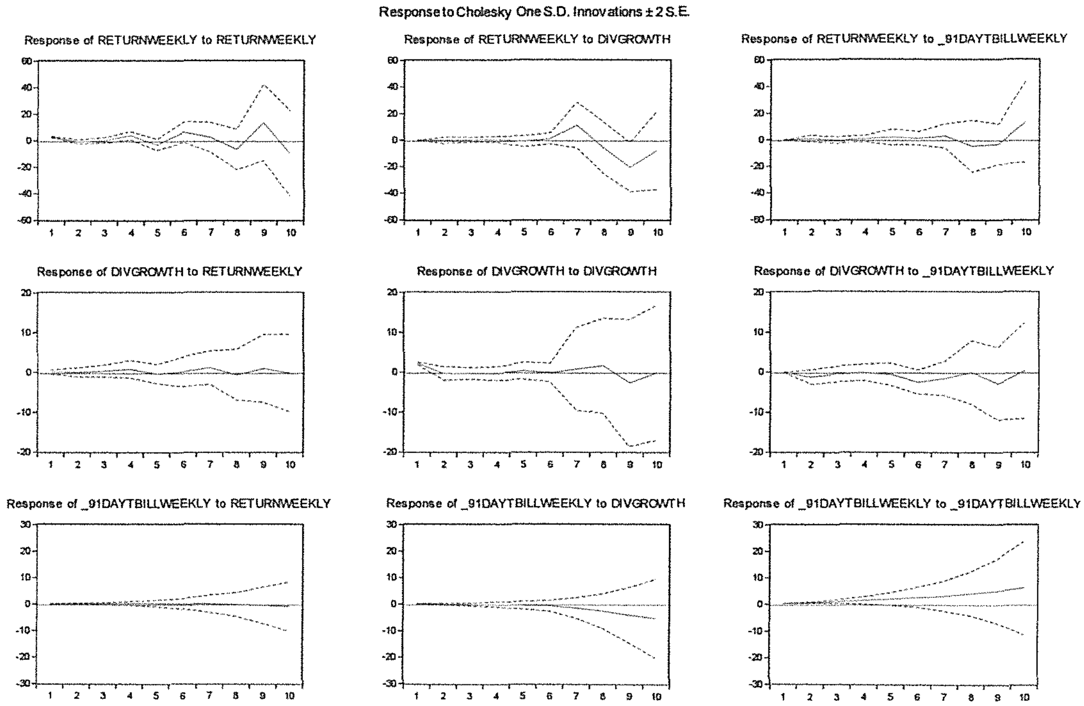


Figure 5: Impulse Response functions of the three variables: NSE 20 weekly returns, weekly dividend growths and the 91 day T Bill weekly rates, for the weekly VAR model with 26 lags.

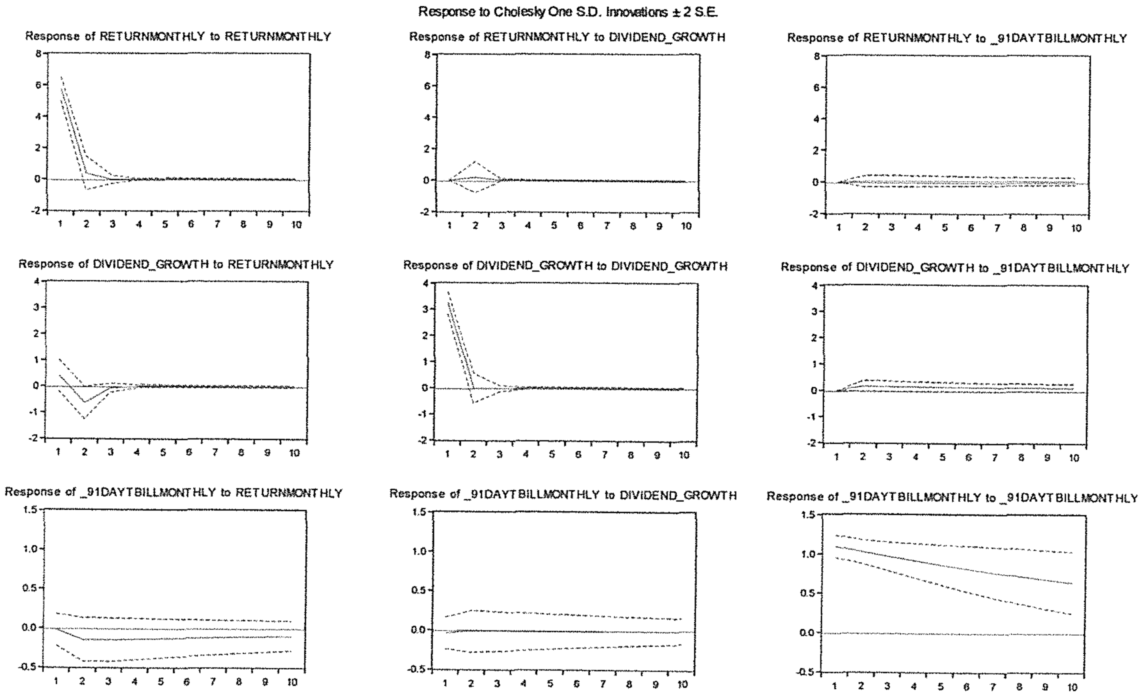


Figure 6: Impulse Response functions of the NSE 20 monthly returns, monthly dividend growths and the 91 day T Bill monthly rates.

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