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Bad beta, good beta and stochastic volatility in an inter-temporal asset pricing model for the Kenyan stock market

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Bad Beta, Good Beta and Stochastic Volatility in an Inter-temporal Asset Pricing Model for the Kenyan Stock Market

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Submitted in partial fulfillment of the requirements for the Degree of Masters of Science
(MSc) in Mathematical Finance at Strathmore University

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June 2018

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Abstract

The study seeks to investigate whether bad beta (sensitivity to cash-flow news), good beta (sensitivity to discount rate news) and volatility news are significantly priced in the Kenyan stock market. A comparison of the 3 models is done: 2-beta pricing model (with cash-flow news and discount rate news as risk factors), a 3- beta model (including volatility news) and a 4-beta model (including covariation risk in cash-flow and discount rate news). The findings from the study suggest that news terms related to cash-flows, discount rates, volatility and the covariation of cash-flow news and discount rate news are all significantly priced in the Kenyan Market. There is evidence that Kenyan investors are highly risk averse, more so towards cash-flow news, than they are to discount rate news. Similarly, the premium charged for volatility news is just as high as that attached to cash-flow news. Investors also attach a significant but relatively smaller premium to the risk due to covariation between cash-flow news and discount rate news.

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1 Chapter One: Introduction

Empirical literature on asset-pricing has grown amenable over the past century, using the first order conditions of utility functions of long term and short term investors alike. The advent of the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) brought to the forefront of the discussion the beta. The intuition behind the CAPM is that investors who perceive an efficient market only price the beta, which captures an asset's sensitivity to the mean variance-efficient market portfolio.

The asset pricing empirical arena took a notable turn after Merton's (1973) Inter-temporal Capital Asset Pricing Model (ICAPM), a linear factor model that imposed tight restrictions on the state variables included in a model attempting to predict asset returns. The sensibility of the ICAPM was in its proclamation that risk and return have a conditional relationship through time, rather than a static one, as the Sharpe & Lintner (1963) CAPM argues.

Economic theory is/was very silent on the variables that should/could be included in such a model, with a presently unanswered question "What are the fundamental risk factors that could be used to predict an asset's return?". According to Cochrane (2001), this exercise could very easily become a "fishing expedition". In the ICAPM, the inclusion of state variables is only justifiable only in the case that they forecast changes in the distribution of future income or specifically, for this study, returns.

More than 2 decades later, empirical literature that sought to question the validity of the Sharpe Lintner CAPM in capturing the cross-sectional variation of stock returns arose. Leading this discussion is Fama and French (1993, 2014) 3-Factor Model and 5-Factor Model respectively. The two authors suggest that in addition to the beta, firm-specific fundamentals including book-to-market ratios (leverage), size (market capitalization), profitability and investment hold significance in the prediction of cross sectional stock return variation.

The consideration of alternative risk factors in asset return predictability studies has sought answers to puzzles in finance; small cap stocks having higher average return compared to larger cap stocks, value stocks outperforming growth stocks, low beta stocks having higher average returns than their higher beta counterparts, etc. The empirical performance of these small, value and low beta stocks has thus long driven portfolio allocations by investors driven by the incentive of higher returns. In an attempt to decipher

how investors should rationally measure the risks of stock market investments, Campbell (1991) derives intuition from a dividend growth model which suggests that stock price dynamics are brought on by two risk factors: news about future dividends (cash flow news) and news about future returns (news about discount rates). The model is built on the foundations of rational expectations of investors and the changes of these expectations thereof. The results suggest that volatility in news about future dividends accounts for at least 33% of the variance in unexpected stock returns.

In a similar fashion, Campbell and Vuolteenaho (2004), attempt to explain the size and value effects on portfolio selection in an inter-temporal asset pricing framework. Their argument is that these two news terms should have different implications on a rational investors portfolio decisions. Specifically, bad news about future cash-flows and future discount rates (increase) cause a fall in the value of the portfolio. However, increase in future discount rates could also be associated with an improvement in future investment opportunities.

As such, the study breaks down the CAPM beta into a “bad beta” and a “good beta”. The bad beta arises from news about cash flows, whereas the good beta arises from news about the discount rates. The model suggests that investors should demand a higher risk premium for assets that covary positively with cash-flow news, compared to those that covary with discount rate news; the “loss” is somewhat dulled in the latter. Their results suggest that the value, small cap and low beta stocks tend to have higher bad betas as compared to growth, large cap and high beta stocks respectively, explaining the higher cross-sectional returns. Campbell and Vuolteenaho (2004) show that in an inter-temporal capital asset pricing model, the price of risk for the good beta should equal the variance of the market return, whereas the price of risk for the bad beta should be γ times greater, where γ is the investor’s coefficient of relative risk aversion.

This discussion of the good vs bad variety of beta is the one of the key prongs in this study. The systematic risk in this study arises from variations in cash-flows and discount rates. We seek to estimate the price of the risk attached to these variations in Emerging and Frontier Equity Markets in Africa. However, a weakness of this discussion on “good” and “bad” beta, is its failure to accommodate the impact of stock return volatility on asset returns. Any investigation of the variation of stock return needs to be augmented by the time variation in volatility of the stock returns to make for a complete inter-temporal analysis of portfolio choice of investors.

The importance of stochastic volatility as a risk factor is underscored further in a follow up paper by Campbell, Giglio, Polk & Turley (2017), a study which extends the 2-Beta model into a 3-Beta ICAPM that seeks to provide a derive investor's pricing of cash flow news, discount rate news and news about stochastic volatility. Their study relies on the first order conditions of an investor with recursive preferences as proposed by Epstein-Zin (1989, 1991). In this regard, this study also seeks to estimate the risk premium attached to stochastic volatility. A comparative analysis is also carried out, evaluating the performance of the 2-beta and 3-beta models in pricing test assets in each of these markets.

The risk premia estimation approach suggested by Campbell and Vuolteenaho (2003) and similarly, by Campbell, Giglio, Polk & Turley (2017) is a two pass estimation approach, where, the parameters of a Vector Autoregressive (VAR) Model are first estimated and then transformed into news terms. The VAR system seen in these studies includes financial asset indicators including the real market return, the Expected Market Variance, the 91-day Treasury Bill Rate, log of the S&P 500 price-smoothed earnings ratio (PE), The Default Spread (difference between the log yield on Moody's BAA and AAA bonds) and the Small-stock Value Spread. The second pass regression estimates the betas which are then used to fit the cross section of asset returns in a GMM estimation generating risk premia estimates for the news terms.

In this study, we also consider a representative investor with Epstein-Zin preferences and follow the SDF solution offered by Campbell, Giglio, Polk & Turley (2017) in decomposing the innovations in the SDF into the three risk components representing cash-flow risk, discount rate risk and stochastic volatility. However, the study uses a Macro- Vector Auto Regression (VAR) Model to describe the shocks in the expected equity returns and the volatility of the returns, where the state variables include: Real Market Return, Expected Market Variance, 91-Day Treasury Bill Rate and Exchange Rate (against US)\$\$. The inclusion of volatility in the VAR factor model allows heteroskedasticity to affect and be affected by the other state variables. Since the VAR model provides a series of shocks that relate to the variables in the VAR system, these shocks (including that to volatility) will be used to construct the news terms which will be key in the cross-sectional analysis.

1.1 Problem Statement

Empirical literature on asset pricing and optimal portfolio choice of long term investors has long studied the risk premium that provides a rational risk averse investor with an appropriate incentive to hold the certain assets over others. At the helm of this debate is the difficulty that the CAPM faces in explaining cross-sectional variations in returns of growth vs value stocks, small-cap vs large cap stocks, low beta vs high beta stock etc. Empirical literature taking into consideration fundamental and macroeconomic risk factors in the pricing of assets in an inter-temporal setting has made a valiant effort in explaining cross-sectional and inter-temporal price variations of assets.

However, standard models of asset pricing have still failed to capture the cross-sectional price variations in these markets. As a result, portfolio diversification into these markets has proven to be a challenge. The puzzle grows thicker, as even with the evidenced low factor exposures, it is observed that these markets have high expected returns! (Bekaert and Harvey (2002)). Therefore, this study constructs risk factors from innovations (shocks) that capture relevant variations in 1) stock market returns and 2) the volatility of these returns, in an effort to investigate whether these risk factors are significantly priced in the Kenyan Equity market. This contributes to knowledge as to how rational investors should measure the risks of stock market investments.

1.2 Research Objective

The objective of this study is two fold:

1. To estimate price of risk due to variations in news about cash flows, news about discount rates and volatility news
2. To compare the pricing performance of a 2-beta model, 3-beta model and 4-beta model (with covariation in discount rate news and cash-flow news) in the Kenyan Equity market.

1.3 The Nairobi Securities Exchange: A Frontier Market

Nairobi Securities Exchange — formerly known as the Nairobi Stock Exchange is tasked with the oversight of security listing, delisting and regulation of trading. The NSE 20-

Share Index (NSE 20) has long been used as the benchmark index used for equity trading in Kenya. This was established in 1964 and has come to represent the 20 best performers in the market. An alternative index is the NSE All Share Index (NASI), aimed at reflecting the total market value of all stocks that are traded on the exchange. As at end of 2017, the NSE had 63 companies listed.

Equity trading volumes, which contribute to 54% to the NSE Group total revenue, registered an increase of 22% in 2017, moving from KShs 5.8 billion in 2016 to KShs. 7.1 billion in 2017. Profit after tax increased by 19%, and this is attributed mainly to the higher equity turnover. The prediction of the NSE-20 market returns in this study is based on a macro VAR with the lagged market returns, short term Treasury Bill Rates, Foreign Exchange Returns and Conditional Variance of the returns. The trend of the 91 day Treasury bill interest rates remained relatively stable during the third quarter of 2017 averaging at 8% with a decline noted. The foreign exchange market has remained stable in 2017 and the shilling strengthened against the Dollar. The NSE-20 market returns as used in the study effectively capture the variations in cash-flows and variations in discount rates. The Treasury Bill Rates as a predictor of market returns capture the information about risk related to the discount rate. The FX returns are also used to predict stock market returns, capturing changes in firm value associated with cash-flow variations due to currency shocks.

1.4 An Inter-temporal Model with Stochastic Volatility

1.4.1 Derivation of a Convenient Identity for the SDF

In this section, we provide a model description of the stochastic discount factor in an Inter-temporal framework that incorporates Stochastic Volatility. The derivation is provided by Campbell, Giglio, Polk, & Turley (2017). The inter-temporal asset pricing framework assumes as a representative agent with recursive Epstein-Zin preferences. The value function of such an investor takes the form below:

$$V_t = \left[(1 - \delta)C_t^{\frac{1-\gamma}{\theta}} + \delta(E_t[V_{t+1}^{1-\gamma}])^{1-\theta} \right]^{\frac{\theta}{1-\gamma}} \quad (1)$$

where C_t is consumption and the preference parameters are the discount factor δ , the risk aversion coefficient γ and the elasticity of inter-temporal substitution (EIS) ψ . For convenience, $\frac{1-\gamma}{1-\frac{1}{\psi}}$ is defined as θ

The stochastic discount factor can be written as:

$$M_{t+1} = \left(\delta \left(\frac{C_t}{C_{t+1}} \right)^{\frac{1}{\psi}} \right)^{\theta} \left(\frac{W_t - C_t}{W_{t+1}} \right)^{1-\theta} \quad (2)$$

Where W_t is the market value of the consumption stream owned by the agent and includes the current consumption C_t

The log return on wealth r_{t+1} can be defined as $\ln \left(\frac{W_{t+1}}{W_t - C_t} \right)$, whereas the log consumption wealth ratio h_{t+1} can be defined as $\ln \left(\frac{W_{t+1}}{C_{t+1}} \right)$. The log of the SDF can be written as:

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{t+1} \quad (3)$$

which is a function of consumption growth, and the log return on wealth r_{t+1} .

The gross return on wealth can be written as:

$$1 + R_{t+1} = \frac{W_{t+1}}{W_t - C_t} = \left(\frac{C_t}{W_t - C_t} \right) \left(\frac{C_{t+1}}{C_t} \right) \left(\frac{W_{t+1}}{C_{t+1}} \right) \quad (4)$$

Taking logs to the specification above, this can be defined as:

$$r_{t+1} = -z_t + \Delta c_{t+1} + h_{t+1} \quad (5)$$

where we define $z_t = \ln \frac{W_t - C_t}{C_t}$ and the future value of a consumption claim as $h_{t+1} = \ln \frac{W_{t+1}}{C_{t+1}}$

The identity in the equation above can therefore be used to write the log SDF expression conveniently without consumption:

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} z_t + \frac{\theta}{\psi} h_{t+1} - \gamma r_{t+1} \quad (6)$$

Taking innovations to the log of the SDF described, we can specify the innovations as (focus on second equality):

$$\begin{aligned} m_{t+1} - E_t m_{t+1} &= -\frac{\theta}{\psi} (\Delta c_{t+1} - E_t \Delta c_{t+1}) + (\theta - 1) (r_{t+1} - E_t r_{t+1}) \\ &= \frac{\theta}{\psi} (h_{t+1} - E_t h_{t+1}) - \gamma (r_{t+1} - E_t r_{t+1}) \end{aligned} \quad (7)$$

The second equality makes use of the expression $r_{t+1} - E_t r_{t+1} = (\Delta c_{t+1} - E_t \Delta c_{t+1}) + (h_{t+1} - E_t h_{t+1})$ to substitute consumption out of the SDF.

1.4.2 Solving the SDF with the Imposition of Log-Normality

Assuming that the asset return and all the state variables to be introduced in the model are jointly log-normal, then the log return on the wealth portfolio must satisfy:

$$0 = \ln E_t[\exp\{m_{t+1} + r_{t+1}\}] = E_t[m_{t+1} + r_{t+1}] + \frac{1}{2} \text{Var}_t[m_{t+1} + r_{t+1}] \quad (8)$$

We can then substitute the log SDF in equation (6) into the asset pricing equation (8), and thereafter multiply by $-\psi$ to obtain an explicit expression for z_t , which can be written as:

$$z_t = \psi \ln \delta + (\psi - 1) E_t r_{t+1} + E_t h_{t+1} + \frac{\psi}{2} \text{Var}_t[m_{t+1} + r_{t+1}] \quad (9)$$

We can approximate the relationship between h_{t+1} and z_{t+1} by taking a log-linear approximation about \bar{z} :

$$h_{t+1} \approx \kappa + \rho z_{t+1} \quad (10)$$

Where the log-linearization parameter $\rho = \frac{\exp(\bar{z})}{1 + \exp(\bar{z})} \approx (1 - \frac{C}{W})$

Recall $z_t = \ln \frac{W_{t+1} - C_{t+1}}{C_{t+1}}$ as defined as the ratio of invested wealth to consumption and the log ratio of wealth to consumption as $h_{t+1} = \ln \frac{W_{t+1}}{C_{t+1}}$. The two are closely related. In fact when EIS, ψ is equal to 1, the log linear relationship between the two holds exactly. Using equation (9) and (10), we can obtain an expression for h_{t+1} :

$$h_{t+1} - E_t h_{t+1} = \rho [z_{t+1} - E_t z_{t+1}] \quad (11)$$

$$\begin{aligned} &= (E_{t+1} - E_t) \rho \left((\psi - 1) r_{t+2} + h_{t+2} + \frac{\psi}{2} \text{Var}_t[m_{t+2} + r_{t+2}] \right) \\ &= (\psi - 1) (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} + \frac{1}{2} \frac{\psi}{\theta} (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \text{Var}_{t+j}[m_{t+1+j} + r_{t+1+j}] \end{aligned} \quad (12)$$

$$= (\psi - 1) N_{\mathbf{DR}, t+1} + \frac{1}{2} \frac{\psi}{\theta} N_{\mathbf{RISK}, t+1}$$

The above specification in equation 12, is that used in Campbell and Voulteenaho (2004), with the assumption of homoskedasticity in the model. The notation $N_{\mathbf{DR}}$ specifies news about discount rates and the notation $N_{\mathbf{RISK}}$ describes the revisions in the expectations of the future risk, which is the sum of the log return plus the log SDF. In particular, we can express news about discount rates as:

$$(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$$

This considers that news about discount rates are associated with *changes in expectations of discount rates*. News about cash flows, as discussed, relate to changes in expectations of cashflows (for example, dividends). As such we can express news about cash-flows as:

$$(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \delta d_{t+1+j}$$

where d_{t+1} is the log dividend paid by the stock, δ indicates a one period change in dividends.

The two news terms (cash-flow news and discount rate news) contribute to unexpected stock returns such that:

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

The above indicates that news about cash-flows is the sum of unexpected returns ($r_{t+1} - E_t r_{t+1}$) and news about discount rates

The final step is to substitute the expression 12 back into equation 7, and using the argument provided above on the relation between NCF and NDR, to generate the following expression for the SDF:

$$\begin{aligned} m_{t+1} - E_t m_{t+1} &= -\gamma[r_{t+1} - E_t r_{t+1}] - (\gamma - 1)N_{\text{DR}, t+1} + \frac{1}{2}N_{\text{RISK}, t+1} \\ &= -\gamma N_{\text{CF}, t+1} - [-N_{\text{DR}, t+1}] + \frac{1}{2}N_{\text{RISK}, t+1} \end{aligned} \quad (14)$$

The equation above expresses the log SDF in terms of the market return and news about future variables. There are three priced factors in the model: news about market return (cash flow news) with a price of γ , negative news about discount rates with a price of 1 and news about future risk with a price of $-\frac{1}{2}$. The price of risk for cash flow news is γ times greater than the price of risk for negative discount rate news. This explains why betas related to cash flow news are intuitively referred to as *bad betas*, whereas those related to negative discount rate news are referred to *good betas*.

2 Chapter Two: Literature Review

2.1 Asset Pricing: Background and Alternative Models

According to Sharpe, 1964, one of the main problems facing those attempting to predict the behaviour of capital markets is *“the absence of a body of positive microeconomic theory dealing with conditions of risk”* Markowitz developed an analysis based on the expected utility maxim and proposed a general solution for the portfolio selection problem. The Sharpe-Lintner CAPM version converted this mean-variance efficiency model into a market-clearing asset-pricing model. All investors have homogenous expectations on the distributions of returns and may borrow or lend unrestrictedly at a risk-free rate. The Capital Asset Pricing Model decomposes a portfolio’s risk into systematic and unsystematic risk. The marketplace compensates investors for taking systematic risk but not for taking unsystematic risk.

The empirical record of the CAPM in terms of its ability to explain cross sectional variation in stock returns has been quiet poor, according to Fama & French (2004), *“poor enough to invalidate the way it is used in applications”*. Tests of the CAPM go as far back as Fama & MacBeth, 1973, whose study tests the relationship between average return and risk for New York Stock Exchange common stocks. Instead of estimating a single cross-section regression of average returns on betas, they estimate cross-section regressions for each time period of returns on betas. They took the coefficients in each time periods regression and averaged them in an effort to price beta. They found that high beta stocks tend to have high average returns as compared to low beta stocks. This and other studies, such as Black Jensens and Scholes (1972), laid the foundation for the pricing of risk in an attempt to explain the cross-sectional variation in asset returns.

More recent tests, both cross-sectional and time series, have attempted to price risk factors associated with firms such as size, earnings to price, debt to equity, and the book to market ratio (B/M) whose explanatory power not captured by beta in the SLB model. These studies confirm the now-recognized empirical flaws in both the Sharpe-Lintner and the Black versions of the CAPM. The evolution of studies of this nature broke ground with studies such as Basu, 1977, tests for the empirical relationship between earnings’ yield, firm size and returns on the common stock of NYSE firms. The results from the study indicated that portfolios of high (low) earnings yield securities trading on the NYSE appear to have earned higher (lower) absolute and risk-adjusted rates of return,

on average, than portfolios consisting of randomly selected securities.

Stattman, 1980, and Rosenberg, Reid, & Lanstein, 1985, also document that stocks with high book-to-market equity ratios (B/M, the ratio of the book value of a common stock to its market value) have high average returns that are not captured by their betas. Similarly, Fama & French's, *The Cross Section of Expected Returns*, 1992, concluded that book to market equity ratios and size of firms provided a simple and powerful characterization of the cross section of the average stock market returns, in that smaller stocks and stocks with higher book-to-market ratios have higher average returns.

Campbell & Shiller, 1998, consider firm earnings as an information variable in forecasting future dividends in a Vector Auto Regression framework. Using price earnings ratio and the dividend price ratio as forecasters of the market using aggregate annual US data from 1871-2000, their study aimed at investigating what component of stock returns can be predicted using the information in a VAR system i.e to answer whether the dividend-price ratio forecasts future dividend movements as required by the random-walk theory, or whether it instead forecasts future movements in stock prices. Their study concluded that the dividend-price ratio has little forecasting power for stock price changes over the next year.

2.2 Inter-temporal Asset Pricing Models

2.2.1 Background

This consideration that there are additional variables, other than the beta specified by SLB, which can possibly explain the cross sectional variation of stock returns has long been studied with various alterations to the CAPM being introduced with time. One of the most important and revolutionary class of modifications to the CAPM is the Inter-temporal Capital Asset Pricing models (ICAPM) by Merton (1973a). The models are collectively known for their ability to allow for inter-temporal decision making as opposed to single period frameworks as was the construct in the CAPM and the Mean Variance Framework from which the CAPM follows. The ICAPM is based on equilibrium arguments where the risk factors considered are market wealth and state variables. As a multi-factor conditional beta pricing model, the ICAPM is often related to the Arbitrage Pricing Theory, the difference being the specification of the type of risk factors to be used in the pricing.

2.2.2 Cash-Flow News and Discount Rate News

One such paper that uses an inter-temporal angle to explaining the cross-sectional variation of stock returns is Campbell (1991), whose study poses an intuitive question as to how rational investors should measure the risks of stock market investments. This study derive intuition from a dividend growth model which suggests that stock prices are caused by two risk factors: news about future dividends (cash flow news) and news about future returns (news about discount rates). The two risk factors are derived from a VAR framework. The analysis in this paper is quite different from Campbell and Shiller (1988) as he does not focus on forecasting dividends, just stock returns. The study finds that in US stock market data, news about future returns and covariance between news of future stock returns and expected dividends are significant contributors to the variations observed in stock returns.

In a follow up study, Campbell (1993) derives a formula for risk premia estimation without consumption. The study takes an approach that simplifies the multi-period asset pricing setting of an Epstein Zin investor with recursive preferences. Portfolio choice and asset pricing problems in a multi-period setting have an added complexity, in that the Bellman equation (value maximization problem) is highly non linear. The study assumes that the variation in the consumption wealth ratio is small, which simplifies the problem to a log-linear approximation, as has been seen in the derivation of the SDF problem above. This simplification also leads to a simple closed form expression that relates the risk premia of securities to their covariances with news about risk factors, in particular, news about future returns. The results indicate that the risk premia of assets is determined by the coefficient of relative risk aversion, and is related to the news about future returns and the covariance of the asset returns with the market return.

Bekaert & Harvey (1995) took a slight revision to Merton (1973) ICAPM by considering the relationship between national equity index returns using as a global market portfolio, which was proxied by the U.S market, particularly, the New York Stock Exchange (NYSE) returns. This came to be known as the International CAPM. In their analysis, the excess return of each individual market to the global market is assessed, the global market portfolio being the systematic source of risk. The analysis aims to establish why different national indices have different expected returns, by considering time varying levels of integration into the global capital market system

Lamont & Polk (1999) also take a different approach to this question of valuation of security returns. The hypothesis in this study is that diversified firms have lower values than portfolios of single segment firms. This effect of diversification is claimed to be due to differences in future cash-flows and future returns generated by diversified firms. By examining the difference between future returns on diversified firms and single segment firms, Lamont & Polk attempt to test whether the variation in the values of these firms is associated with news about future returns from either of these firms. Their results finds that not only is the diversification discount puzzle related to the news about future returns, it is also explained by news about future cash-flows, thus feeding into the literature of cross-sectional variation of asset returns.

Building from Campbell (1993), Campbell and Vuolteenaho (2004), attempt to explain the size and value effects in portfolio allocation in an inter-temporal asset pricing framework. The main innovation in this paper was the breakdown of the CAPM beta into a “good beta” and a “bad beta”, with the rationale that the bad beta of the market portfolio should have a higher price of risk compared to the good beta. The bad beta arises from news about cash flows, whereas the good beta arises from news about the discount rates. The bad beta causes a fall in the value of the portfolio when investors receive news that the future cash flows of the portfolio will decline. The good beta similarly causes a fall in the value of the portfolio, due to news that discount rates will go up. However, the increase in discount rates is also associated with improved future investment opportunities.

Their results suggests that the value stocks and small stocks tend to have higher bad betas as compared to growth stocks, providing an explanation for their higher cross-sectional returns. Campbell and Vuolteenaho (2004) suggest that in inter-temporal capital asset pricing model (ICAPM) the price of risk for the discount-rate beta should equal the variance of the market return, while the price of risk for the cash-flow beta should be γ times greater, where γ is the investor’s coefficient of relative risk aversion.

2.3 Stochastic Volatility in Inter-temporal Asset Pricing

The drawback of the above models is that there is an assumption of homoskedasticity of stock returns, i.e. they have constant variance over time. Stochastic volatility has been widely explored in literature with documented effects on portfolio choice of investors. Chacko & Viceira (2005) examine the optimal portfolio demand for stocks when investors

have access to both risk-less and risky assets. Their findings suggest that the inter-temporal hedging demand by risk averse investors is negative when the time varying precision of returns is low and when the correlation between volatility and stock returns is negative. Time-varying volatility studies after Engle's (1982) originating paper on ARCH, have come up with variants of the Generalized Autoregressive Heteroskedasticity Model (GARCH) of (Bollerslev 1986), in which conditional volatility of returns is fore-casted using lagged shocks to returns and its own lags.

The assumption of homoskedasticity in asset pricing leads to a tunnel view of the risk premia estimation ignoring the variations in risk (stochastic volatility) as a potential risk factor in itself. Chen (2003) develops and estimates an ICAPM where the conditional means of the returns are estimated using a Vector Auto-Regression (VAR) and a Multivariate GARCH (1,1) model (composite VAR-MGARCH) is used to capture conditional variances. The resulting conditional covariances from the estimation are then used in the risk premium estimation equation. The inclusion of the time varying volatilities adds some robustness to the description of an investment opportunity set, with the endgame being to assign a "*hedge demand driven*" risk premium to an asset when this opportunity set goes awry.

An improvement to Chen's (2003) approach is suggested in Sohn (2010). One of the criticisms cited by Sohn is with regards to the exclusion of the volatility term in the VAR system. Given Chen (2003) use of the VAR-MGARCH, the volatility term cannot be included in the mean equation. As such, it is impossible to assess how volatility affects and is affected by the remaining state variables in the VAR. Sohn (2010) alternatively estimates a GARCH-MIDAS model (Engle, Ghysels, and Sohn (2013)) where both long run and short run stock market volatility are obtained separately and treated as observable variables.

Nardari and Scruggs (2005) introduce a model whereby the covariance matrix of the Vector Autoregression follows a multivariate stochastic volatility process (VAR-MSV). The model permits the decomposition of the unexpected real return into three risk factors including; news about future dividends, news about future returns and a covariance term. One of the key motivation of the paper is to explore if the stochastic volatility (extracted from a Bayesian VAR estimation) is driven by news about future dividends and news about future real returns. Secondly, they study to what extent the stochastic volatility components explain variations in future returns. Their findings indicate that time

variations in volatility of news about future returns is very significant in explaining the volatility of the stock market.

Campbell, Giglio, Polk & Turley (2017) extend the model of Campbell and Voulteena (2004) to incorporate stochastic volatility in the specification of the risk premia equation. The paper models volatility of all shocks to the VAR as an additional element of the system, improving the fit to cross sectional variations of value vs growth stocks and small vs large cap stocks. They estimate the expected market variance in the model by constructing realized variance of daily returns and regressing the series against the remaining state variables to establish the “predicted variance”

2.4 Estimation of Risk Premia: Portfolios vs Stocks

The estimation and evaluation of asset pricing models in empirical literature has long developed and used econometric techniques that seek to answer questions surrounding the estimation of parameters, estimating standard errors of the parameters, and testing the model. It is a common belief that asset pricing models should hold for all assets, regardless of whether the assets are individual stocks or portfolios. On this front especially, empirical literature has taken considered very different approaches in specifying the test assets used in cross-sectional asset pricing model tests. First, researchers have followed Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), among many others, to group stocks into portfolios and then run cross-sectional regressions using portfolios as base assets.

A natural strategy for the estimation of parameters and evaluation of the models was suggested by Black-Jensen-Scholes (1972), who attempted a cross section test on the CAPM using a single cross section used monthly data on stocks from the NYSE. The evidence they presented indicated the expected excess return on an asset is not strictly proportional to its β . The empirical results in their paper also suggests that the returns on different securities can be written as a linear function of two factors i.e. β_j and $1 - \beta_j$, the former being the coefficient for the market returns and the latter on a zero beta portfolio. They concluded that these provide sufficiently strong evidence to warrant rejection of the traditional form of the model. They then show how the *cross-sectional tests are subject to measurement error bias*, and provided a solution to this problem through grouping procedures. They generated a range of beta coefficients as well as to attenuate estimation errors by grouping stocks into 10 portfolios.

Fama & MacBeth, 1973, also test the relationship between average return and risk for New York Stock Exchange common stocks. In the Fama-Macbeth study, the sample average excess returns Z_{it} represents the empirical counterpart of the expected return on asset i , $E(R_i) - R_f$. The observed excess returns Z_{it} could for any time period t will be included in forming the dependent variable. This introduces the concept of Fama-Macbeth regressions. In running the FM regressions the cross section regression equation is:

$$Z_{it} = \gamma_0 + \gamma_{1t}\beta_i + \nu_{it}$$

According to Fama & MacBeth, 1973, it is possible to obtain estimates of γ_0 and γ_1 for every time period i.e. as many regressions as there are time periods. OLS can be applied to generate γ_{0t} and γ_{1t} for each time period. The estimates are averaged to obtain the FM estimates. By doing this FM were addressing the inference problem caused by correlation of the residuals in cross-section regressions. The correlation arises as the average value relies on past return values each. Instead of estimating a single cross-section regression of average returns on betas, they estimate cross-section regressions for each time period of returns on betas. They took the coefficients in each time periods regression and averaged them.

This discussion of early works in the area of asset pricing lead us to a key discussion that holds weight in the methodological approach used in this study. The use of portfolio/groupings of stocks on the basis of certain characteristics such as size, book to market ratio, liquidity, etc have gained a lot of popularity in asset pricing. The key reason for the study of risk premia using portfolios rather than individual stocks is due to reduction in error in variables.

This discussion on error-in-variable was very well demystified by Blume (1970, p156) who gave the original motivation for creating test portfolios of assets as a way to reduce the errors-in-variables. In particular, the discussion revolves around investor assessments of portfolio allocation on the basis of two parameters: α_i and β_i . If the errors in these assessments were independent amongst different assets, then, they would become even smaller when the assets are in a portfolio. Intuitively, the errors would offset each other, and idiosyncratic risk eventually becomes lower leading to more efficient estimates of *factor loadings*.

However, a litany of literature surrounding the use of characteristic portfolios in the estimation of risk premia was initiated by Lo & Mackinlay (1990). The argument in their

study is that tests of asset pricing models could be a simple case of data snooping, especially when we see properties of the stocks, such as size, being used to construct the test assets. According to Monte Carlo simulations used in the analysis, and further empirical illustrations, they find that this kind of data snooping actually has significant effects into the reliability of inferences. Shanken (1992) provided a comprehensive study, analyzing the statistical properties of the Fama-Macbeth procedure under the assumption of conditional homoskedasticity of returns. Using a GLS (generalized-least-squares) estimation method in the second pass regression, the study conjectured that it may not be necessary to group securities into portfolios to address the EIV.

Similarly, Brennan, Chordia and Subrahmanyam (1998) find that EIV problem can be avoided without grouping securities into portfolios by using individual risk-adjusted returns as the explained variable in asset pricing mode tests. This is as long as the risk factors are expressed as excess returns on traded assets. However, it cannot be said that the merits of this approach have been well studied in literature, in comparing performance with an analysis where portfolio grouping procedures has not been examined in the literature.

Following this discussion, studies such as those by MacKinlay and Richardson (1991) show how parameters of the Capital Asset pricing Model can be estimated by applying the GMM to its beta representation. The study also shows that when the GMM estimator and the maximum likelihood method are used under conditional homoskedasticity they are equivalent, however under heteroskedasticity, the MLE is biased. An advantage of using the GMM is that it allows estimation of model parameters in a single pass thereby avoiding the error-in-variables problem.

The use of the GMM became well recognized in finance and, particularly asset pricing, with the study by Hansen and Singleton (1982) on the Consumption Based Asset Pricing Model. Subsequent developments in the area have quickly rendered it a reliable and go-to econometric methodology in linear beta pricing models, and its robustness is fed from its allowance for stock returns and other economic time series to be serially correlated, leptokurtic, and conditionally heteroskedastic.

The discussion on the use of portfolios in linear asset pricing models has been well picked up in recent years by Ang, Liu & Schwarz (2017). According to their study, the fewer the portfolios used in the Fama-Macbeth regression, the lower the standard errors of the portfolio factor loadings. A fewer number of portfolios indicates that there will be

less cross-sectional variation in betas that are used to form the risk premia estimates. Therefore, this means that the standard errors of the estimates of risk premia increase when portfolios are used, rather than when all listed stocks are used. The argument put forward is that creating portfolios to reduce estimation error in the factor loadings does not lead to smaller estimation errors of the factor risk premia.

This argument has been brought on even more strongly by Jeegadesh et al (2017), who argue that with portfolios in risk premia estimation, the issue of test power arises since dimensionality is reduced; i.e., variation in returns of portfolios is possible with fewer explanatory variables than it is when using individual assets. Also of importance is that forming portfolios to reduce EIV can hide important cross-sectional characteristics.

Similarly, according to a study by Lewellen, Nagel, and Shanken (2010) point out that this sorting on characteristics imposes a significant factor structure in the test asset used. Lewellen et al. (2010) show as a result that even factors that may not be strongly correlated with the sorting characteristics could be found to be significant in explaining cross-sectional variation in returns, without regard to the plausibility of theoretical foundations of such relationships.

Jeegadesh et al (2017) suggest the use of an instrumental variables approach in the estimation of risk premia associated with risk factors. This is done in an effort to overcome the shortcoming that are associated with sortings into portfolios, while still reducing the error in variables problem that come with using individual assets. A similar approach is used in this study, motivated by the small number of stock listed on the market.

2.5 Research Gaps and Discussion of Literature Review

The literature discussed above highlights the ground covered in the measurement of risk by rational investors. The concept of good beta vs bad beta that stemmed from the derivation by Campbell (1991) sought to explain the cross sectional variation in stock returns. The idea is that investors will assign a higher premium to cash flow risk (bad beta) as compared to discount rate risk due to the permanency of the cash-flow shocks to expected returns as opposed to the latter's shocks. Discount rate risk is argued to have a transitory effect on asset returns, according to Campbell & Vuolteenaho (2004)

The inclusion of stochastic volatility in the debate is a paramount step towards a better description of asset returns. In a setting without time-varying volatility, it is argued by

Campbell, Giglio, Polk & Turley (2017) that this leads to an incomplete inter-temporal analysis of portfolio choice of investors, because changes in expectations of future risk drive the return premium that investors require. The time-varying precision of returns is reduced in an environment of stochastic volatility, and as such, the inter-temporal hedging demands of investors are much higher, leading to higher excess returns.

The study of cross sectional variation in emerging and frontier markets is a growing field of literature that seeks to identify risk factors that investors in these markets consider significant in their pricing of assets. It has been noted that portfolio diversification to these markets has proven a challenge because standard models of asset pricing used in developed markets have failed to capture the cross-sectional price variations in these markets. A key research gap exists here. This study is related to existing empirical literature on cash flow risk and discount rate risk. The pricing of volatility risk in stock markets came out very clearly in BKSJ (2014) study and more literature has followed suite, seeking to look as far as having time varying risk premia estimates.

An important methodological aspect for this stud is the use of individual stocks to test the asset pricing mode, as opposed to using portfolios, as most papers in the asset pricing realm have done since Fama and French (1993). Because of this, we use an instrumental variable drive estimation of the Fama-Macbeth procedure to reduce the Error-in-Variables.

3 Chapter Three: Methodology

3.1 Research Design

The study adopts a descriptive research design. The empirical analysis carried out in this paper seeks to investigate the risk premiums associated with specific news factors (innovation-driven) in an African Equity markets. The design is also comparative by seeking to estimate the risk premiums and evaluating the performance of a 2-beta, a 3-beta and a 4-beta pricing model in a Frontier Equity market.

3.2 Population and Sampling

The study considers the Kenyan stock market for analysis. We seek to investigate the inter-temporal pricing of news terms in a frontier market. The study considers the market index in the country as proxy for the mean variance efficient market portfolio. The Nairobi Securities Exchange has 63 listed companies (active and inactive) as at 2017. The listed companies in will be used in the construction of the test assets.

3.3 Data Analysis

3.3.1 VAR Estimation

The VAR class of models has received immeasurable attention in economic forecasting applications using multiple time series data sets. The models have been used as alternatives to univariate models by providing simultaneous parameter estimates required in many macroeconomic and policy spaces. The model was proposed by Sims (1980), motivated by the use of macroeconomic theory to justify the inclusion of a set of variables in explaining a dependent variable. The attraction of these models came in the fact that the specification of exogenous variables in the specifications is unnecessary in order to forecast the endogenous variables. Since VARs frequently require the modeller to estimate many parameters, there is a common problem of over-parameterization of the models. the parameters to be estimated use few observations, using up many degrees of freedom.

Assuming the economy is described by a first order Macro VAR of the form:

$$Z_{t+1} = \bar{z} + \Gamma_t(Z_t) + \sigma_t \varepsilon_{t+1} \quad (15)$$

where Γ is a 4×4 matrix of VAR parameters, $\sigma_t \varepsilon_{t+1}$ is a 4×1 vector of residuals with ε_{t+1} having a covariance matrix Σ , and Z_{t+1} is a vector of 4×1 state variables that includes: Real Market Return, 91-Day Treasury Bill Rate, Exchange Rate against US\$ and the Market Variance.

The selection of the most appropriate order of the VAR model has been done in this study using a VAR selection test.

The inclusion of the Market Variance term in the VAR is expected to provide a description of the predictability relationship between volatility and the remaining state variables in the system. This approach is motivated by the work of Sohn (2014), which treats volatility as an observable factor and, after its estimation using a GARCH-MIDAS model, includes it in the VAR System. The Market Variance term in the VAR system is estimated using a suitable GARCH model using monthly real market return data.

3.3.2 Estimation of News Terms

In this section, the study shows how the news terms (Cash flow news, discount rate news, and stochastic volatility news) are constructed from the error term of the VAR specification discussed in the section above.

The study defines two ($n \times 1$) vectors, e_1 and e_4 , whose elements are all zero except for a unit first element in e_1 and unit fourth element in e_4 . This is because the returns on the NSE-20 index and the corresponding conditional volatility are the first and fourth state variables in the VAR system.

According to Campbell (1991) and Campbell and Voulteenaho (2004), the vector of residuals is assumed to be homoskedastic, with a constant covariance matrix to match Σ , where $\Sigma_{11} = 1$. The assumption in their study is that a scalar variable σ_t^2 which is the conditional variance of the market returns governs the shocks to the entire system, i.e those on the real market return and the other state variables. This structure allows us to generate news terms specified as below:

$$N_{DR,t+1} = e_1' \rho \Gamma (I - \rho \Gamma)^{-1} \sigma_t \varepsilon_{t+1} \quad (16)$$

$$N_{CF,t+1} = (e_1' + e_1' \rho \Gamma (I - \rho \Gamma)^{-1}) \sigma_t \varepsilon_{t+1} \quad (17)$$

where we define $\lambda_{DR} \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$ as the weight used to transform the residuals from the VAR into the news terms (specifically the cash flow news and the discount rate news)

Recall that the log SDF (from the log-linearization) makes it a linear function of the state variables, making all shocks to the log SDF proportional to σ_t . Therefore, the news about risk is proportional to market variance, σ_t^2 ($Var_t[m_{t+1} + r_{t+1}] \propto \sigma_t$). The scaled conditional variance $Var_t[\frac{m_{t+1} + r_{t+1}}{\sigma_t}]$ is thereby equal to a constant ω which does not depend on the state variables.

$$N_{RISK,t+1} = \omega\rho e'_4(I - \rho\Gamma)^{-1}\sigma_t\varepsilon_{t+1} = \omega N_{V,t+1} = \omega\sigma_t^2 \quad (18)$$

where we define $\lambda_V = \rho(I - \rho\Gamma)^{-1}$ s the weight used to transform the residuals from the VAR into the news of future risk term.

The elements of the vector λ_{DR} and λ_V capture the importance of each state variable in VAR system in forecasting future market returns and future market volatilities i.e future investment opportunity sets. If a particular element, λ_n of λ_{DR} or λ_V is large and positive (negative), then a shock to n^{th} variable in the VAR is an important piece of good news about future investment opportunities.

The above derivation is extracted from the model specification of Campbell (1991) and Campbell and Voulteenahe (2004).

3.3.3 Risk Premia Estimation: Derivation of Moment Conditions: Campbell, et al (2017)

This subsection shows how the moment conditions used in the GMM estimation are derived from the expectation of the sum of the stochastic discount factor and the log return on wealth. The derivation of moment (Euler) conditions is needed in GMM estimation for identification in parameter estimation.

The innovations in the log SDF had been expressed earlier as:

$$m_{t+1} - E_t m_{t+1} = -\gamma N_{CF, t+1} - [-N_{DR, t+1}] + \frac{1}{2} N_{RISK, t+1}$$

Under lognormality, the general asset pricing model can be expressed as:

$$0 = \ln E_t \exp\{m_{t+1} + r_{i,t+1}\} = E_t\{m_{t+1} + r_{i,t+1}\} + \frac{1}{2} Var_t\{m_{t+1} + r_{i,t+1}\} \quad (19)$$

We can rewrite the above as:

$$0 = E_t[m_{t+1}] + E_t[r_{i,t+1}] + \frac{1}{2} Var_t[m_{t+1}] + \frac{1}{2} Var_t[r_{i,t+1}] + Cov_t(r_{i,t+1}, m_{t+1} - E_t m_{t+1}) \quad (20)$$

There are two substitutions to be made to the equation (20) above:

First the conditional mean of the log stochastic discount factor is zero, therefore, we can express the covariance term as: $Cov_t(r_{i,t+1}, m_{t+1} - E_t m_{t+1}) = E_t(r_{i,t+1}, m_{t+1} - E_t m_{t+1})$

It is also possible to link the expected log returns (adjusted by the variance) to the expected gross level of returns by: $E_t[r_{i,t+1}] + \frac{1}{2}\sigma_{it}^2 \approx \ln(E_t R_{i,t+1})$

If the expected gross return $E_t R_{i,t+1} - 1$ is close to 1, we have it that : $\ln E_t R_{i,t+1} \approx (E_t R_{i,t+1} - 1)$, therefore

$$E_t[r_{i,t+1}] + \frac{1}{2}\sigma_{it}^2 \approx (E_t R_{i,t+1} - 1)$$

$$E_t R_{i,t+1} - 1 = -E_t[m_{t+1}] - \frac{1}{2}Var_t[m_{t+1}] - E_t(r_{i,t+1}, m_{t+1} - E_t m_{t+1}) \quad (21)$$

Writing equation (21) in terms of the risk premium (given a reference asset j),

$$E_t R_{i,t+1} - E_t R_{j,t+1} = -E_t[(r_{i,t+1} - r_{j,t+1})(m_{t+1} - E_t m_{t+1})] \quad (22)$$

$$E_t R_{i,t+1} - E_t R_{j,t+1} = -E_t[(r_{i,t+1} - r_{j,t+1})(-\gamma N_{\mathbf{CF}, \mathbf{t}+1} - [-N_{\mathbf{DR}, \mathbf{t}+1}] + \frac{1}{2}\omega N_{\mathbf{V}, \mathbf{t}+1})] \quad (23)$$

This can also be written in covariance form:

$$E_t R_{i,t+1} - E_t R_{j,t+1} = \gamma Cov[(r_{i,t+1} - r_{j,t+1}), N_{\mathbf{CF}, \mathbf{t}+1}] + Cov[(r_{i,t+1} - r_{j,t+1}), N_{\mathbf{DR}, \mathbf{t}+1}] - \frac{1}{2}\omega Cov[(r_{i,t+1} - r_{j,t+1}), N_{\mathbf{V}, \mathbf{t}+1}] \quad (24)$$

From the above equation, an important implication on the price of risk of the three news terms is made: *the price of risk associated with cash-flow news is γ , that associated with discount rate news is 1. Therefore the price of risk of cash-flow news is γ times greater than that associated with discount rate news. That associated with stochastic volatility, N_{RISK} is $\frac{1}{2}$. By proxy then, the price of risk associated with N_V , from which N_{RISK} is derived, is $\frac{\gamma}{2}$.*

3.3.4 Fama-Macbeth Procedure using GMM

The covariance terms seen above can be easily transformed into beta measurements. The estimation of betas represents the first stage of the Fama-Macbeth regression, a cross sectional regression method used to estimate risk premia in asset pricing. However,

before the estimation of the risk premia, we consider a number of test assets and the excess returns associated with these assets. The test assets considered in this study include 45 stocks listed on the Nairobi Securities Exchange. The use of individual stocks as test assets is an ongoing empirical discussion, one that was kicked off by a study by Lo and Mackinlay (1990). This study suggests that tests of asset pricing models on the basis of characteristic sorted portfolios is *border line data snooping*.

This discussion has been picked up in recent years by Lewellen, Nagel, and Shanken (2010), Ang, Liu & Schwarz (2017) and Jeegadesh et al (2017). Lewellen, Nagel, and Shanken (2010) point out that this sorting on characteristics imposes a significant factor structure in the test asset used. Lewellen et al. (2010) show as a result that even factors that may not be strongly correlated with the sorting characteristics could be found to be significant in explaining cross-sectional variation in returns, Ang, Liu & Schwarz (2017) suggest that the standard errors of the estimates of *risk premia* increase when portfolios are used, rather than when all listed stocks are used. The argument put forward is that creating portfolios to reduce estimation error in the factor loadings does not lead to smaller estimation errors of the factor risk premia. Jeegadesh et al (2017) argue that with portfolios in risk premia estimation, the issue of test power arises since dimensionality is reduced; i.e., variation in returns of portfolios is possible with fewer explanatory variables than it is when using individual assets. Also of importance is that forming portfolios to reduce EIV can hide important cross-sectional characteristics.

On the basis of this empirical literature, we use 45 individual stocks listed on the NSE in estimating the factor loadings. Even so, consideration of the estimation method used is key in the analysis,. Jeegadesh et al (2017) suggest the use of an instrumental variables approach in the estimation of risk premia associated with risk factors. This is done in an effort to overcome the shortcoming that are associated with sorting into portfolios, while still reducing the error in variables problem that come with using individual assets. Cochrane (2009) suggests the use of GMM estimation, which allows corrections for autocorrelated and heteroskedastic error terms. Similarly, he also advocates for the use of GMM estimates of expected return-beta models as well, rather than just on basic pricing models that use the SDF. This implies that the Fama-MacBeth becomes invalid for heteroskedastic asset pricing models. GMM provides a simple techniques that estimates parameters under weaker conditions.

In the first pass regression of the Fama -Macbeth procedure, the returns of stocks are

regressed against the news terms, using GMM. The possible presence of heteroskedasticity and serial correlation in the news terms over time is considered, and as such, OLS would lead to inefficient estimates of the betas (OLS requires i.i.d errors, independent of the factors). Specifically, suppose we have a model of the form:

$$R_t = \alpha + \beta_{NCF}NCF_t + \beta_{NDR}NDR_t + \beta_{NV}NV_t + \varepsilon_t$$

where R_t is the vector of returns (dependent variables), β_k is a factor loading, ε is a $n \times 1$ vector of residuals such that $E(\varepsilon_t|X_t) = 0$, and $Var(\varepsilon_t|X_t) = \sigma_t^2$.

According to Cochrane (2001), a simpler analytical representation of the standard errors can be generated by assuming that the error are i.i.d, the error terms are independent of the factors, and the factors are uncorrelated over time as well. . The assumption that the errors and risk factors are uncorrelated over time means the lead and lag terms can be ignored. The assumption that the errors are independent from the factors f_t simplifies the terms in which ε_t and f_t are multiplied as shown in the moment conditions below. The moment conditions required for this estimation are highlighted below:

$$g_T(b) = \begin{pmatrix} E_T[R_t - \alpha - \beta_{NCF}NCF_t - \beta_{NDR}NDR_t - \beta_{NV}NV_t] \\ E_T[R_t - \alpha - \beta_{NCF}NCF_t - \beta_{NDR}NDR_t - \beta_{NV}NV_t]NCF_t \\ E_T[R_t - \alpha - \beta_{NCF}NCF_t - \beta_{NDR}NDR_t - \beta_{NV}NV_t]NDR_t \\ E_T[R_t - \alpha - \beta_{NCF}NCF_t - \beta_{NDR}NDR_t - \beta_{NV}NV_t]NV_t \\ E[\bar{R} - \gamma_{NCF}\beta_{NCF} - \gamma_{NDR}\beta_{NDR} - \gamma_{NV}\beta_{NV}] \end{pmatrix} = 0$$

The second pass estimation for the estimation of the risk premia takes the form below, similar to the cross-sectional regression equation formulated by Fama-Macbeth (1973):

$$\bar{R}_i = \lambda_0 + \lambda_{CF}\hat{\beta}_{i,CF} + \lambda_{DR}\hat{\beta}_{i,DR} + \lambda_V\hat{\beta}_{i,V} \quad (25)$$

where \bar{R}_i is the time series mean for the excess returns of asset i . The estimation of the λ s is an unrestricted three-beta model that allows free risk premium estimation for news about cash flows (cash flow risk), news about discount-rate (discount rate risk), and stochastic volatility and carried out using GMM.

Estimation via GMM is much easier in this cross-sectional model due to the derived moment condition representation of the asset pricing equation below:

$$E_t[R_{i,t+1} - R_{j,t+1} - (r_{i,t+1} - r_{j,t+1})(-\gamma_{NCF,t+1} - [-N_{DR,t+1}] + \frac{1}{2}\omega N_{V,t+1})] = 0 \quad (26)$$

4 Chapter Four: Data Analysis Results

4.1 VAR(1) Model Results

The framework introduced in the methodology assumed that the economy is described by a first order Macro-VAR of the form:

$$Z_{t+1} = \bar{z} + \Gamma_t(Z_t) + \sigma_t \varepsilon_{t+1} \quad (27)$$

where Γ is a 4×4 matrix of VAR parameters, $\sigma_t \varepsilon_{t+1}$ is a 4×1 vector of residuals with ε_{t+1} having a covariance matrix Σ , and Z_{t+1} is a vector of 4×1 state variables that includes: Real Market Return, Market Variance, 91-Day Treasury Bill Rate and Exchange Rate against US\$.

However, an appropriate VAR order is selected based on information criteria further below.

The inclusion of the Market Variance term in the VAR is expected to provide a description of the predictability relationship between volatility and the remaining state variables in the system. The market variance is extracted from an appropriate GARCH model.

The study, after consideration of possible asymmetric properties of volatility, fits a GARCH (1,1) model to the returns on the NSE-20, from which we extract the conditional variance of the series. An alternative APARCH (Asymmetric Power ARCH) Model is also considered (APARCH holds as special cases the GJR-GARCH, the Taylor-Schwert-GARCH and the T-ARCH model). The APARCH specification allows an asymmetric specification of the volatility of returns by including a leverage term in the variance equation. However, on comparison, the GARCH (1,1) specification is found to have the lowest AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) of all four specifications considered, and is thus selected for modeling the volatility of the NSE-20 Returns. The conditional variance of the NSE-20 returns was extracted from the model:

The GARCH (1,1) analysis presumes a normal distribution for the returns. The results are shown below:

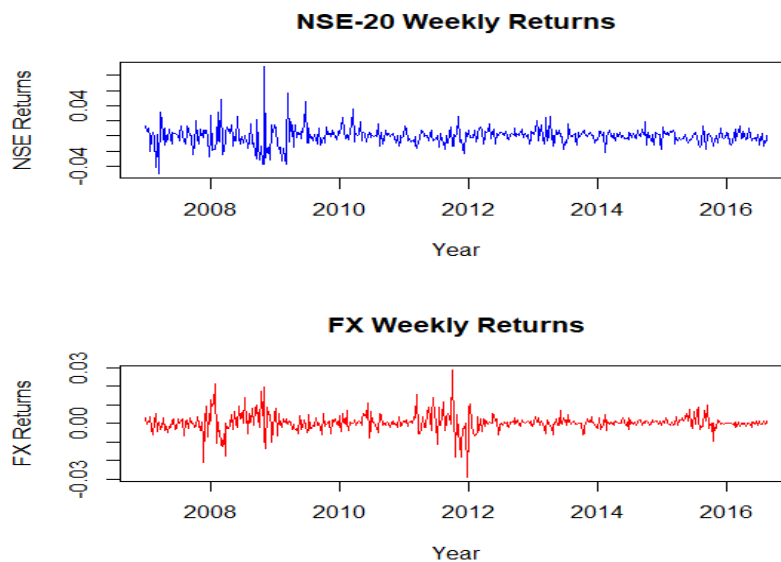
$$y_t = \mu_t + \varepsilon_t, \Rightarrow \varepsilon_t = \sigma_t v_t \Rightarrow v_t \sim N(0, 1)$$
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \Rightarrow \omega > 0, \alpha > 0, \beta \geq 0$$

The results of the GARCH (1,1) are shown below:

	Estimate	Std Error	t value	$Pr(> t)$	
mu	-0.0001	0.0004	-0.1870	0.8520	
omega	0.0000	0.0000	2.3140	0.0207	*
α_1	0.1654	0.0419	3.9490	0.0001	***
β_1	0.8082	0.0427	18.9290	0.0000	***
Log-likelihood	1612.863				
	AIC	BIC	SIC	HQIC	
	-6.4098	-6.3762	-6.4099	-6.3966	

The time series evolution of the four variables is shown below; the data ranges from beginning of 2007 to September 2016:

Figure 4.1: NSE-20 Returns and FX Returns

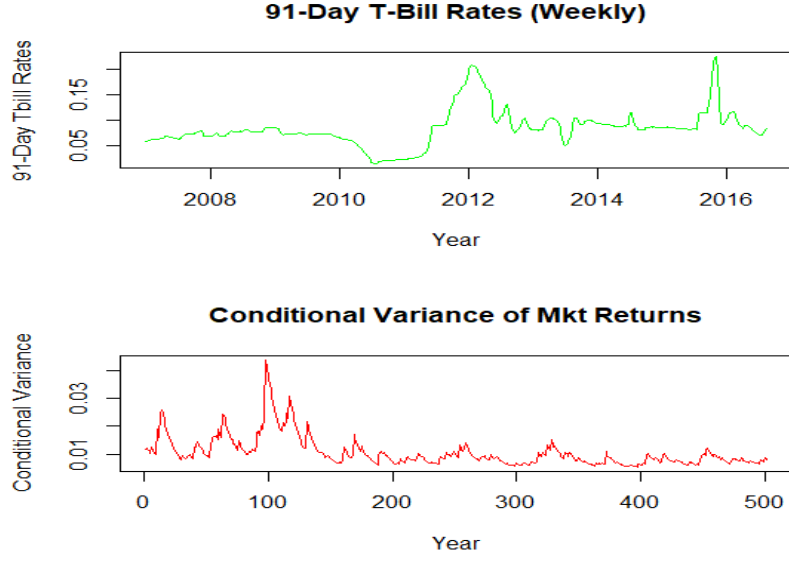


On the basis of four Information Criteria (AIC, BIC, HQ, FPE), a VAR (1) model specification is selected (results for VAR selection test in appendix). The table shows the parameter estimates for the first-order VAR model. The state variables in the VAR include the log return on the NSE-20 index, the conditional variance on the index, the three-month Treasury-Bill Rate and the log return on the Forex Rate against the US\$:

Table 4.2: VAR Estimation Results: NSE-20 Returns and NSE-20 Conditional Variance

Mkt Returns	Estimate	Std. Error	t value	Pr(> t)	Significance
Mkt Returns.L1	0.02703	0.04539	0.59600	0.55200	
FX Returns.L1	-0.09320	0.11337	-0.82200	0.41100	
91-Day TBill Rate.L1	-0.00373	0.01459	-0.25500	0.79900	
Conditional Variance.L1	-0.10694	0.09884	-1.08200	0.28000	
const	0.00104	0.00176	0.59100	0.55500	
Multiple R-Squared	0.00472				
	Estimate	Std. Error	t value	Pr(> t)	
Mkt Returns.L1	0.03167	0.00627	5.05500	0.00000	***
FX Returns.L1	0.02158	0.01565	1.37900	0.16900	
91-Day TBill Rate.L1	-0.00057	0.00201	-0.28300	0.77700	
Conditional Variance.L1	0.95769	0.01364	70.19700	0.00000	***
const	0.00050	0.00024	2.03800	0.04200	*
Multiple R-Squared	0.90950				

Figure 4.2: 91-Day T-Bill Rates and Conditional Variance



The results shows that all four VAR state variables have great predictive ability to predict conditional variance of returns on the aggregate stock market.. The R-squared for the returns estimation is quite low, however, it is considered reasonable, given the weekly data used. The impulse response of the state variables in the system is shown in the Appendix.

4.2 Cash-flow News, Discount Rate News and Variance News

In transforming the residuals from the above VAR into the news terms, we use transformation functions that map the residuals into cash flow news, discount rate news and stochastic volatility.

As had been explained in Section of the methodology, the following functions are considered:

$$\begin{aligned}
 N_{DR,t+1} &= e'_1 \rho \Gamma (I - \rho \Gamma)^{-1} \sigma_t \varepsilon_{t+1} \\
 N_{CF,t+1} &= (e'_1 + e'_1 \rho \Gamma (I - \rho \Gamma)^{-1}) \sigma_t \varepsilon_{t+1} \\
 N_{RISK,t+1} &= \omega \rho e'_2 (I - \rho \Gamma)^{-1} \sigma_t \varepsilon_{t+1} = \omega N_{V,t+1} = \omega \sigma_t^2
 \end{aligned}$$

Tabled below are the functions used to map their shocks to the news terms, in particular: $e'_1 + e'_1 \lambda_{DR}$ for cash flow news, $e'_1 \lambda_{DR}$ for discount rate news, and $e'_4 \lambda_V$ for variance news, where $\lambda_{DR} \equiv \rho \Gamma (I - \rho \Gamma)^{-1}$, and $\lambda_V \equiv \rho (I - \rho \Gamma)^{-1}$. As earlier mentioned, the elements

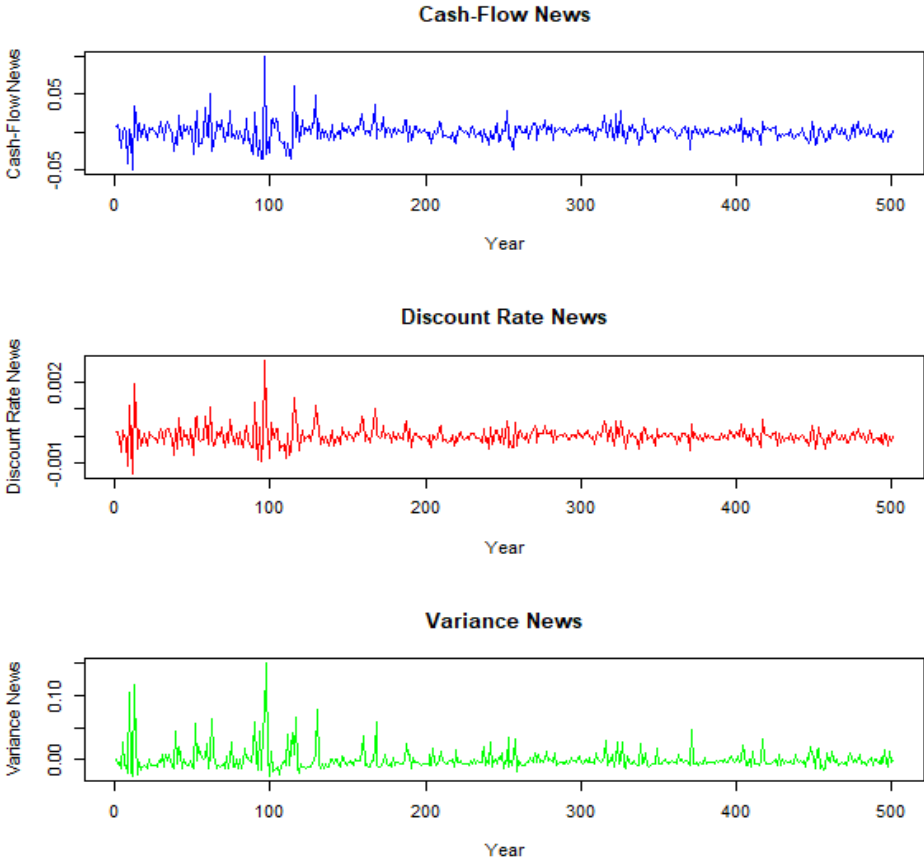
of the vector λ_{DR} and λ_V capture the importance of each state variable in VAR system in forecasting future market returns and future market volatilities i.e future investment opportunity sets. If a particular element, λ_n of λ_{DR} or λ_V is large and positive (negative), then a shock to n^{th} variable in the VAR is an important piece of good news about future investment opportunities. The ρ is set to 0.95, similar to that in Campbell, et al (2017).

Table 4.3: Transformation Functions for VAR Residuals to News Terms

	Mkt Return shock	FX Return shock	T-Bill Rate shock	Cond Var shock
NDR lambda	0.02566	0.01042	0.00008	0.10640
NCF lambda	1.02566	0.01042	0.00008	0.10640
NV lambda	0.30195	0.18610	-0.14616	10.02375

The time series plot of the news terms is shown in the plot below:

Figure 4.3: News Terms evolution from 2007 to 2016



The table below shows the correlation between the three news terms:

A relatively high positive correlation of 0.61 between discount rate news and volatility

Table 4.4: Correlations between News Terms

	NDR lambda	NCF lambda	NV lambda
NDR lambda	1.00000	0.85031	0.60961
NCF lambda	0.85031	1.00000	0.11823
NV lambda	0.60961	0.11823	1.00000

news. According to Bansal, Kiku, Shaliastovich & Yaron (2014), the correlation observed is in line with economic intuition. It is expected that both news terms will be high in recessions, and low during booms. Looking at discount rates in an economy, they are largely driven by expectation of future premium, rather than the risk free rate. Similarly, market volatility news are also driven by expectations of economic uncertainty. In this way then, the two news terms are jointly driven by common economic time series dynamics, mostly those that indicate economic performance. As such, the correlation is expected. The correlation survives the relatively high frequency data used (weekly), contrary to the argument the four authors provide indicating that the positive correlation only holds at lower frequencies, such as yearly data.

4.3 Fama-Macbeth Procedure: First and Second Stage using GMM

The study uses 45 stocks listed on the Nairobi Securities Exchange in the first pass regressions, and the corresponding vector of factor loadings on the news terms in the second pass regressions. As discussed in Chapter 3, the two stages are estimated using GMM which allows for heteroskedastic and autocorrelated error terms.

The analysis first estimates the betas to cash-flow news, discount rate news and stochastic volatility news for each of the stocks. This is the first stage of the Fama- Macbeth Regression. It is important to note in this analysis, that the discount rate beta considers the covariance between the return on the stock and bad news about discount rates (discount rates going up). The second stage treats that estimated betas as independent variables, regressed in a GMM environment against average stock returns over the sample years used in the study. The coefficients from the estimation are the associated risk premia for each of the news terms.

The results from a 2-beta model with 2 risk factors; news about cash-flows and news about discount rates, and a 3-beta model that takes volatility news into account are provided below

Table 4.5: 2-Beta Model Risk Premia Estimation (Cash-Flow news & Discount Rate News)

	Estimate	Std Error	t value	Pr(> t)	Initial Values
Intercept	-0.2457	0.0168	-14.6550	0.0000	-0.2056
γ_{NCF}	0.4477	0.0023	197.2400	0.0000	0.4495
γ_{NDR}	0.0094	0.0004	25.3170	0.0000	0.0097
J-Test: degrees of freedom is 3		J-Test	Pr(> t)		
Test	E(g)=0:	26.1690	0.0000		

Table 4.6: 3-Beta Model Risk Premia Estimation (Cash-Flow news, Discount Rate News, Volatility News)

Estimate	Estimate	Std Error	t value	Pr(> t)	Initial Values
Intercept	-0.1431	0.0205	-6.9630	0.0000	-0.1401
γ_{NCF}	0.4005	0.0082	48.6610	0.0000	0.3881
γ_{NDR}	0.0152	0.0009	16.0570	0.0000	0.0136
γ_{-NV}	0.4129	0.0670	6.1657	0.0000	0.4250
J-Test: degrees of freedom is 3		J-test	Pr(> t)		
Test	E(g)=0:	21.7420	0.0000		

The first row of the table 6 above presents the estimates and corresponding statistics for the zero-beta, the second row presents results for the cash-flow news risk premium, the third row for the discount rate news risk premium and the fourth on stochastic volatility news risk premium. All risk premiums estimated as associated with negative (bad) news (decline in cash-flow news, increase in discount rates, increase in stochastic volatility). These are all positive and significant (95% confidence interval), indicating participants are averse to each of the risk factors. The risk premium attached to cash-flow news (42%) is much higher compared to that attached to discount rate news (1.5% for discount

rate news). An asset return that has a positive covariance with its cash-flow shocks is considered risky to an investor, as it pays off when the investor is well off, and fails to hedge appropriately when the investor is experiencing negative shocks to cashflows.

Recalling that discount rate news capture the revisions in expectation about future returns of the market, it is known that a positive shock to the factor represents in an improvement of the investment opportunity set, hence its name “good beta”. The risk premium on the news term is positive and significant. Considering its role as a state variable that reveals the future investment opportunity set, if there was a positive covariance between shocks to discount rate news and returns on the asset, this would imply that a negative shock to discount rate news (presenting deteriorating future investment opportunities) is unlikely to be offset by movements in asset returns.

Consequently, an investor will be concerned about the riskiness of such an asset and will require a higher premium. It can be argued, on the basis of these results, that investors are more averse to cash-flow related risks as compared to discount rate related risks. In light of the risk premia estimates, it is clear that the magnitude of the premium is largely driven by the former. The lower premium associated with discount rate news may be associated with the fact that a negative shock to discount rates does not just represent a deterioration in investment opportunities, but also a capital gain on asset values, hence reducing the premium an investor would require as compensation.

The implied risk aversion coefficient can be calculated from the coefficients as: $\frac{\gamma_{NCF}}{\gamma_{NDR}}$. The implied coefficient from the results is 26.6, which suggests that Kenyan Investors are highly risk averse. According to the derivation of the log SDF provided by Campbell et al (2017) (Refer to Section 1.3.2 equation 14), the price of risk for cash flow news is expected to be γ times greater than the price of risk for negative discount rate news. This implies that the premium to cash-flow news is 26.6 times larger than that on discount rate news. This is consistent with the bad-beta good beta classification given to the two risk factors. The result for the risk aversion coefficient is quite large, relative to the range of 1 to 10 which is considered reasonable in literature on Equity Premium Puzzle (Mehra & Prescott (1985)). Given the significant premiums also observed, especially on cash flow news and volatility news, it is apriori expected that the related risk aversion coefficient be as high as the results suggest.

The risk premium on volatility news is positive and significantly priced, with a premium of 41.3%. This indicates that investors in stocks will require a higher premium from stocks

that have high sensitivities to volatility shocks in the market. Such a stock therefore becomes less valuable. The sign of the risk premium implies that with the existence of the leverage effect (this is the observed tendency of a stock's volatility to be negatively correlated with the stock's returns), the expected return premium on an asset will be lowered, and as such it will be more expensive. The conclusion is that volatility news positively affects the stochastic discount factor by attaching a positive risk premium to it. This finding is in line with studies by Bansal, Kiku, Shaliastovich & Yaron (2014).

The J-statistic provided from the estimation of both models, however, shows that the model fails to correctly price the assets (2-beta model has a J-statistic of 26.1690 and a corresponding p-value of 0.0000. 3-beta model has a J-statistic=21.7420, corresponding p-value=0.0000).

4.4 Risk associated with Covariation of Cash-Flow and Discount Rate News

A related aspect of the literature on bad beta and good beta considers whether returns are exposed to co-skewness risk. Co-skewness considers an asset's ability to mitigate risk due to changes in variation in market returns. The importance of skewness risk was presented by Kraus and Litzenberger (1976) who suggest that skewness is a key risk factor since investors prefer positive skewness, and are averse to negative skewness. They show that risk due to skewness can be split into three: 1) co-skewness with news about cash-flows, 2) co-skewness with news about discount-rates and 3) the covariance between stock return and covariation of cash flow news and discount rate news. The covariation in cash-flow news and discount rate news is the product between $-NCF$ and NDR . This indicates that positive shocks to both news terms present adverse situations for the investors ($-NCF, +NDR$), whereas negative shocks to both are favourable ($-(-NCF), -NDR$).

The first two risk factors (which can be seen to use the third moment) capture the ability of the stock to hedge against risks due to variations in cash flows and discount rates. The third term, covariance of stock return to the covariation in cash-flow news and discount rate news, captures the ability of a stock to hedge co-variation between the cash flows and discount rate components of the stochastic discount factor. The estimated model below includes this last one as a fourth risk factor, covariance to the covariation in cash flow and

discount rate news. We seek to establish whether co-skewness risk is priced significantly in the market. The results are presented below:

Table 4.7: 4-Beta Model: Risk Premia Estimation with Covariation in News Terms

	Estimate	Std Error	t value	$Pr(> t)$	Initial Values
Intercept	-0.0688	0.0178	-3.8716	0.0001	-0.1153
γ_{NCF}	0.3795	0.0075	50.4660	0.0000	0.3790
γ_{NDR}	0.0155	0.0007	21.8940	0.0000	0.0135
γ_{NV}	0.4883	0.0484	10.0830	0.0000	0.4464
$\gamma_{NCF*NDR}$	-0.0006	0.0001	-7.1950	0.0000	-0.0004
J-Test: degrees of freedom is 3					
Test	E(g)=0:	1.73E+01	6.25E-04		

The risk factors are all significant in the estimated model. The first 3 risk factors i.e cash-flow news, discount rate news and volatility news all remain consistent in sign and size of the risk premia estimates compared to the 3-beta model. The risk premia estimate on the covariance of returns with the covariation of cash-flow news and discount rate news is negative and significantly priced in the market. As mentioned, a relatively high covariation in the two news terms implies that bad news about cash-flows covary with bad news about discount rates. In such a market, where the covariation between the two news terms is high, investors would prefer an asset that co-varies positively with the covariation in the news terms such that as the covariation in the news terms increases so do the returns. Similarly, when the covariation in the news terms is low, the returns are low. This gives the investor an asset that pays off when times are bad and does not when times are good. The asset hedges appropriately.

Therefore, the negative risk premium attached to the covariation factor implies that if an asset's returns covary positively with the covariation factor, the premium charged on the asset is reduced, in line with basic foundations of asset pricing models. However, the J-statistic provided from the estimation shows that the model still fails to correctly price the assets (J-statistic of 17.3 and a corresponding p-value of 0.0006.)

5 Chapter Five: Conclusion

In this study, we estimate a closed form inter-temporal model of stock returns in the Kenyan Market that seeks to investigate the significance and size of the risk premium attached to three risk factors that are seen to drive the variation return on the market: revisions in expected cash-flows, revisions in expected discount rates and revisions in volatility expectations. The three factors are seen to represent news terms in cash-flows, discount rates and volatility. The study begins by transforming residuals from a Macro VAR into the news terms. These news terms all come in significantly, using 45 listed stocks from the Nairobi Securities Exchange as the test assets.

Particularly, the risk premium attached to cash-flow news (42%) is much higher compared to that attached to discount rate news (1.5% for discount rate news). According to Campbell and Vuolteenaho (2004), inter-temporal asset pricing theory suggests that the bad beta should have a higher risk premium than the good beta. It can be argued, on the basis of these results, that investors are more averse to cash-flow related risks as compared to discount rate related risks. The implied risk aversion coefficient can be calculated from the coefficients as: $\frac{\gamma_{NCF}}{\gamma_{NDR}}$. The implied coefficient from the results is 26.6, meaning the price of risk for cash flow news is expected to be 26.6 times greater than the price of risk for negative discount rate news. The positive premium attached to cash-flow news is associated with the fact that an asset whose return has a positive covariance with its cash-flow shocks is considered risky to an investor, as it pays off when the investor is well off, and fails to hedge appropriately when the investor is experiencing negative shocks to cash flows. This is consistent with the results in Campbell, Giglio, Polk & Turley (2017) and Campbell & Vuolteenaho (2004)

As concerns discount rate news, the positive premium is suggested to be related to the signals of the investment opportunity set. Considering the role of the discount rate news as a state variable that signals the viability of the future investment opportunity set, a positive covariance between shocks to discount rate news and asset returns would imply that a negative shock to discount rate news (presenting deteriorating future investment opportunities) is unlikely to be offset by movements in asset returns. Consequently, an investor will require a higher premium. Similarly, the risk premium on volatility news is positive and significantly priced, with a premium of 41.3%, indicating that investors will require a higher premium from stocks that have high sensitivities to volatility shocks in the market.

A negative risk premium is estimated for the covariance of returns to the covariation factor. This implies that if an asset's returns covary positively with the covariation factor, the premium charged on the asset is reduced, in line with basic foundations of asset pricing models.

The findings above suggest that news terms related to cash-flows, discount rates, volatility and covariation of cash-flow news and discount rate news are significantly priced in the Kenyan Market. There is evidence that Kenyan investors are highly risk averse, more so towards cash-flow news, than they are to discount rate news. As concerns discount rate news, the premium charged by investors seems to be a compensation for deterioration of future investment opportunities, rather than that for capital losses associated with increasing discount rates. Similarly, the premium charged for volatility news is just as high as that for cash-flow news.

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A Appendix

A.1 APARCH (1,1) Estimation Results

Table A.1: APARCH (1,1) Results

	Estimate	Std Error	t value	$Pr(> t)$	
mu	-0.0002	0.0004	-0.5780	0.5631	
omega	0.0000	0.0000	2.4810	0.0131	*
alpha_1	0.1416	0.0381	3.7190	0.0002	***
gamma_1	0.1659	0.0976	1.7000	0.0891	.
beta_1	0.8350	0.0403	20.7330	0.0000	***
delta	1.6910	0.4170	4.0550	0.0001	***
Log-likelihood	1609.898				
	AIC	BIC	SIC	HQIC	
	-6.3900	-6.3396	-6.3903	-6.3702	

A.2 VAR Estimation Results: FX Returns and TBill Rates

Table A.2: VAR Estimation Results: FX Returns and TBill Rates

FX Returns	Estimate	Std. Error	t value	$Pr(> t)$	
Mkt Returns.L1	-0.04401	0.01804	-2.44000	0.01505	*
FX Returns.L1	0.06376	0.04505	1.41500	0.15761	
91-Day TBill Rate.L1	-0.01434	0.00580	-2.47300	0.01374	*
Conditional Variance.L1	-0.06751	0.03928	-1.71900	0.08630	.
const	0.00221	0.00070	3.15900	0.00168	**
Multiple R-Squared	0.03565				

91-Day TBill Rate	Estimate	Std. Error	t value	$Pr(> t)$	
Mkt Returns.L1	-0.00279	0.02233	-0.12500	0.90100	
FX Returns.L1	0.02805	0.05576	0.50300	0.61500	
91-Day TBill Rate.L1	0.98754	0.00718	137.61200	0.00000	***
Conditional Variance.L1	0.02404	0.04862	0.49400	0.62100	
const	0.00083	0.00087	0.96200	0.33600	
Multiple R-Squared	0.97490				

A.3 Impulse Response Functions

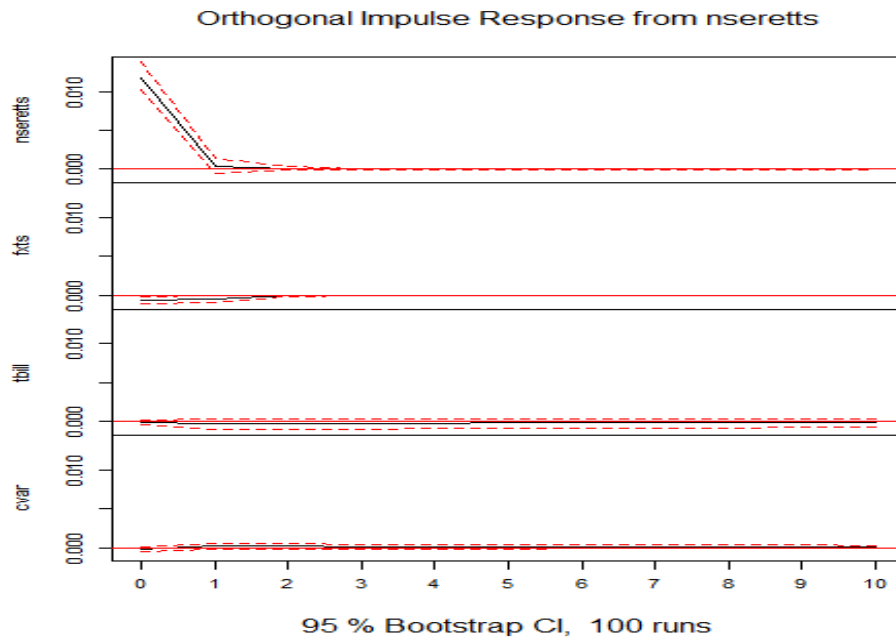


Figure A.1: Impulse Response Function Plot: NSE-20 Returns

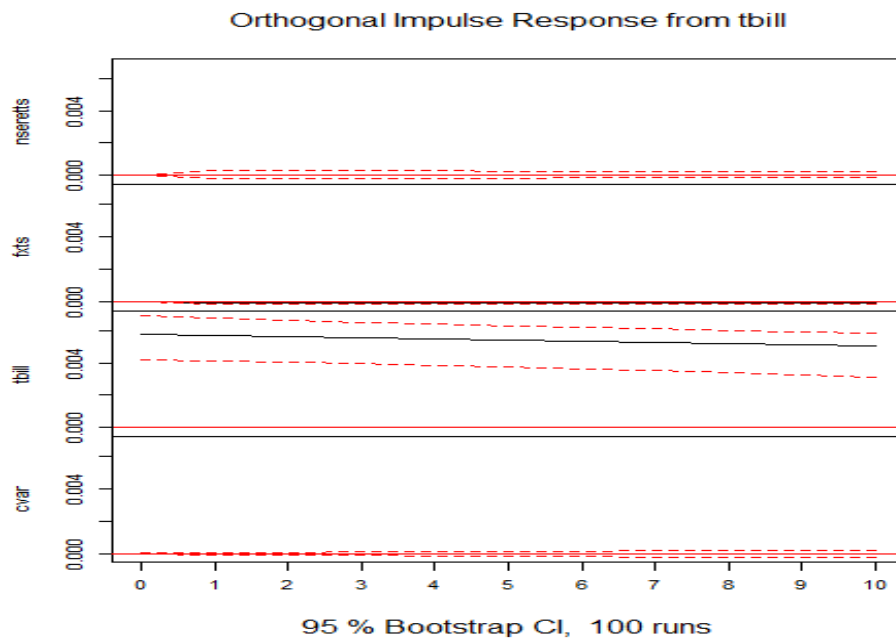


Figure A.2: Impulse Response Function Plot: 91-Day Treasury Bill Rate

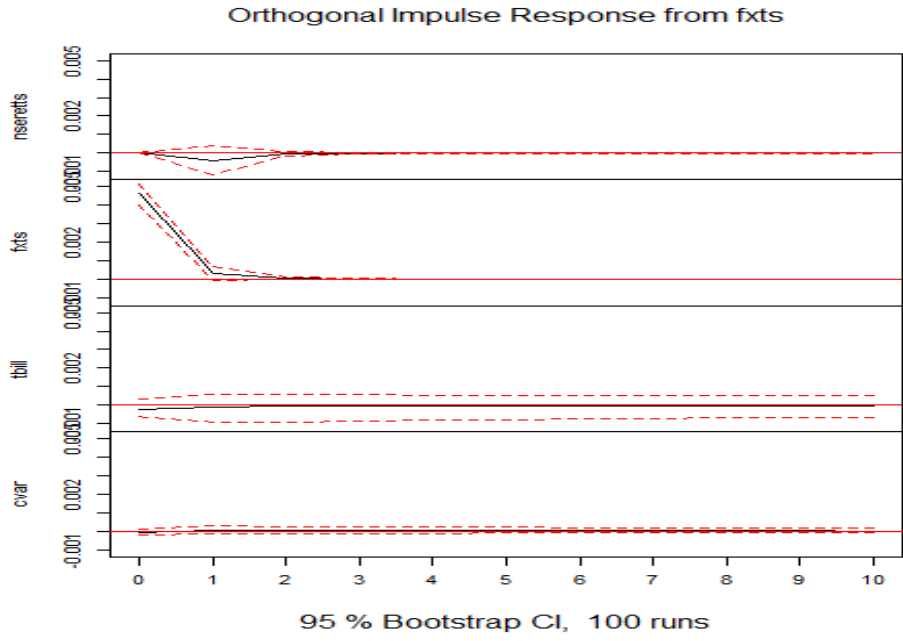


Figure A.3: Impulse Response Function Plot: Kenya Shs. FX Returns

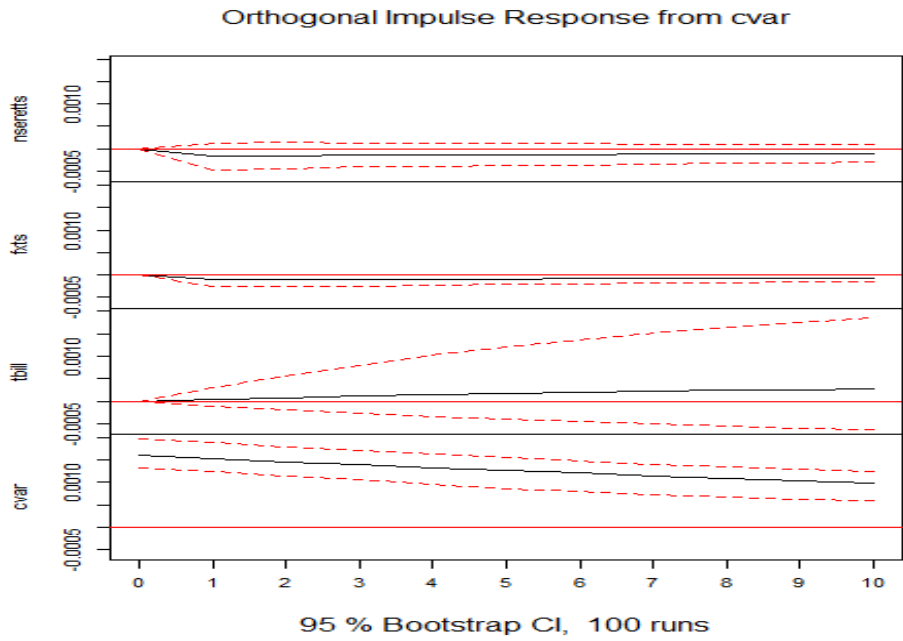


Figure A.4: Impulse Response Function Plot: Conditional Volatility

A.4 Test Assets' Factor Loadings on News Terms

Table A.3: Test Assets and Factor Loadings on News Terms

Company	Sector	Intercept	Beta NCF	Beta NDR	Beta NV
Athi River Mining	Construction	-0.0008	0.1726	20.3471	-0.3152
British American Tobacco	Manufacturing	0.0013	0.5738	-14.5276	0.0862
CFC Stanbic	Banking	0.0000	0.1753	13.9998	-0.2331
Diamond Trust	Banking	0.0007	1.3852	-38.8121	0.4114
East African Breweries	Manufacturing	0.0006	1.9338	-57.7970	0.5345
Kenya Commerical Bank	Banking	-0.0017	1.7180	-41.8875	0.4875
Kenya Power	Energy	-0.0030	0.1097	33.8229	-0.5479
NIC Bank	Banking	-0.0010	1.3784	-26.7012	0.1836
Nation Media Group	Commercial	-0.0008	0.6417	-7.4883	0.0574
Bamburi Cement	Construction	-0.0001	0.0966	6.4668	-0.0828
Barclays Bank Of Kenya	Banking	-0.0018	0.8331	-15.3044	0.0811
Britam	Insurance	0.0005	-0.3275	27.5200	-0.3167
Centum	Investments	-0.0017	0.5866	12.2927	-0.2946
CIC Insurance	Insurance	0.0000	0.1974	-1.2389	0.0156
Cooperative Bank	Banking	0.0003	0.3719	1.8180	-0.0515
Equity Bank	Banking	-0.0011	2.3719	-72.4773	0.7350
Kengen	Energy	-0.0013	0.8967	5.7643	-0.0492
Kenol Kobil	Energy	-0.0019	3.1431	-131.2562	1.4005
Kenya Re	Insurance	0.0002	0.6362	11.0651	-0.0556

Company	Sector	Intercept	Beta NCF	Beta NDR	Beta NV
Standard Chartered Bank	Banking	0.0001	-0.0280	23.5244	-0.3838
Safaricom	Telecommunications	0.0009	1.0305	-25.9976	0.2844
WPP Scangroup	Commercial	-0.0004	1.3908	-37.0855	0.2969
Car & General	Automobiles	-0.0003	0.3971	-5.7998	-0.0497
Carbacid	Manufacturing	100.8683	258.6789	-1567.8060	51.6020
CMC Motors	Automobiles	-0.0022	-1.0055	79.8984	-1.7200
Crown Berger	Construction	0.0000	-0.1659	28.7545	-0.4944
E A Cables	Construction	-0.0016	0.0895	28.1046	-0.4326
Portland Cement	Construction	-0.0013	-0.6144	33.5391	-0.4290
Jubilee Insurance	Insurance	0.0004	0.3559	3.7178	-0.0289
Kakuzi	Agriculture	0.0017	0.8670	-24.6944	0.0840
Kapchorua	Agriculture	-0.0002	-0.2744	13.6688	-0.1835
Limuru Tea	Agriculture	0.0007	-0.3085	11.7749	-0.1249
Marshall East Africa	Automobiles	-0.0013	-0.0536	2.9442	-0.0346
Mumias Sugar	Manufacturing	-0.0032	-0.1760	50.2988	-0.6712
Pan Africa Insurance	Insurance	-0.0007	1.3001	-45.9934	0.3668
Sameer East Africa	Automobiles	-0.0018	0.0167	13.5726	-0.1970
Sasini Limited	Agriculture	0.0006	0.8041	-24.0665	0.0819
Standard Group	Commercial	-0.0007	0.2033	8.4395	-0.2038
TPS East Africa	Commercial	-0.0013	0.9535	-17.1188	0.1743
Uchumi	Manufacturing	-0.0012	-0.3779	26.9827	-0.2768
Williamson Tea	Agriculture	0.0003	-0.4816	28.8601	-0.5618
Eaagads	Agriculture	0.0004	-0.6601	25.0986	-0.1219
National Bank	Banking	-0.0012	0.7558	-4.7757	-0.1323
Kenya Airways	Commercial	-0.0017	-0.6359	47.5891	-0.8905
Total Kenya	Energy	0.0006	1.4690	-3.9009	0.2385