EMPIRICAL TESTING OF ALTERNATIVE OPTIONS MODELS ON NAIROBI SECURITIES EXCHANGE

By

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A Research Project Submitted in partial fulfilment of the requirements for the degree of Master of Science in Finance, University of Nairobi.

May, 2013

DECLARATION

I hereby declare that this study is my original work and effort and that it has not been submitted for a degree in any other University.

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I hereby declare that this study is from the student's own work and effort, and all other sources of information used have been acknowledged. This study has been submitted with my approval.

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DEDICATION

This study is dedicated to my parents. For their endless love, support and encouragement.

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I am most grateful to my Supervisor Dr. Josiah O. Aduda for his guidance, encouragement and enthusiasm. He introduced me to exciting research areas including this study topic, provided me with his brilliant ideas and extremely valuable advice.

I would like to express my gratitude to my loving wife Mary, who has been the greatest inspiration in my life and to my Children Quennell and Quillan.

To all my friends, thank you for your understanding and encouragement in my many, many moments of crisis. Your friendship makes my life a wonderful experience. I cannot list all the names here, but you are always in my mind.

Thank you, Lord, for always being there for me.

ABSTRACT

This study presents a new pricing approach and examines the volatility index by using GARCH-type approximation relation on a security in a local capital market. The originality of this approach is to model the local volatility of the securities to obtain accurate approximations with tight estimates of the error terms. This approach can also be used in the case of pricing options with stochastic convenience yields. The model is applied to Nairobi Securities Exchange (NSE) All Share Index Stock data. From the real market data, the realized volatility is empirically analysed by measuring the deviations of pricing errors. Because of its analytical tractability, the implied parameters are estimated from minimizing the weighted sum of squared errors between the market data.

The study combines the computational knowledge and option pricing theory, to investigate, design and implement a new option pricing approach, by empirically testing the alternative GARCH pricing model, which can process the observed volatilities or market returns to price the equities. The approach could help researchers to test the accuracy of the pricing model or their input volatility, and also can help investor to compare the market with the estimated price to discover the best investment moment. The discussion, methodology and testing are focused on the issues of computational finance.

The findings in this study have evidenced that positive correlation between stock index returns and volatility has two implications. When the stock index return is high, volatility tends to be high. Conversely, when the stock index return is low, volatility tends to be low. The approach of this study can be used to adjust volatility index levels by measuring deviations of pricing errors of future share prices before expiration of each trading period.

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ABBREVIATIONS

ARCH:	Autoregressive Conditional Heteroscedasticity
ATM	at-the-money
CBOE:	Chicago Board Options Exchange
CIR:	Cox-Ingersoll-Ross
CMA:	Capital Markets Authority
EMM:	Efficient Method of Moments
GARCH:	Generalised Autoregressive Conditional Heteroscedasticity
NSE:	Nairobi Securities Exchange
OU:	Ornstein-Uhlenbeck
PDE:	Partial Differential Equation
S&P 500/SPX:	Standard & Poor's Index
SNP:	Semi-Nonparametric
SV:	Stochastic Volatility

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CHAPTER ONE

INTRODUCTION

1.1 Background to the study

1.1.1 Options

Options are derivative contracts where the holder may choose to forfeit the contract. The holder has the right to exercise, but not the obligation. A call option on an underlying asset gives the holder the right to buy the asset at a predetermined price the strike price at a specified time in the future. For a European option, this time point is fixed at the maturity time. The American option allows the holder to buy the asset for the strike price at any time up to the maturity date. The payoff function looks like $V(t) = (S_t - K)^+$, if K denotes the strike price and S_t is the spot price of the underlying asset at the exercise date. The put works in the opposite way of the call, allowing the holder to sell the underlying asset at the strike price. The payoff is $V(t) = (K - S_t)^+$.

The digital or binary option pays out a unit amount on the maturity date if the spot of the underlying asset is above some pre-determined boundary. The payoff function is

$$V(t) = 1_{\{S_T \geq B\}}$$

Where $1_{\{A\}}$ is the indicator function, which takes value 1 if the event A occurs and 0 otherwise. The barrier options toggle payoff on or off when the underlying hits a barrier. One example is the down-and-out digital option. If the underlying spot price hits or crosses a predetermined boundary B up to the maturity date, the option pays out zero. If the spot price trajectory stays above the boundary during the whole time interval the option pays out one. We have,

$$V(t) = 1_{\left\{\inf\limits_{t^* \in [0,t]} S_{t^*} > B\right\}}$$

Similar to the down-and-out is the up-and-out digital option. Its payoff is instead one if the stock price stays below an upper bound and zero if the stock price hits or crosses the upper bound. The barrier options mentioned so far are digital, i.e. they pay either zero or one. A barrier options can have other types of payoffs. A European up-and-out call option for example pays of like a standard European call option, assuming that the stock price stays below the boundary. Otherwise it pays off zero. One of the more common lookback options is the maximum-to-date call. It is almost like a European call, but instead of using the spot price of the underlying asset for exercise, the strike is compared to the maximum of the asset price path up to the date of exercise. A maximum-to-date call has a payoff function of the form $V(t) = max(sup_{t^* \in [0,t]} S_{t^*}$

The Asian option uses the mean level of the spot price process for comparison. The arithmetic Asian call option uses the ordinary arithmetic mean, $\hat{x}(t) = \frac{1}{t-a}\int_a^t x(s)\, ds$ and has the following payout function, $V(t) = (\frac{1}{t-a}\int_a^t S(s)\, ds - K)^+$ and a denotes the point in time from where the mean is taken.

1.1.2 Option Pricing

Options has been considered to be the most dynamic segment of the security markets since the inception of the Chicago Board Options Exchange (CBOE) in April 1973, with more than 1 million contacts per day, CBOE is the largest and business option exchange in the world. After that, several other option exchanges such as London International Financial Futures and Options Exchange (LIFFE) had been set up. Over the last few decades due to the famous work of Black and Scholes, the option valuation problem has gained a lot of attention. In Black and Scholes (1973) seminar paper, the assumption of log-normality was obtained and it application for valuing various range of financial instruments and derivatives is considered essential.

Options form the foundation of innovative financial instruments, which are extremely versatile securities that can be used in many different ways. Over the past decade, option has developed to provide the basis for corporate hedging and for the asset/liability management of financial institutions. Option pricing theory has a long history, but it was not until Black and Scholes presented the first completely equilibrium option pricing model in the year 1973. Moreover, in the same year, Robert Merton extended the Black-Scholes (BS) model in several important ways. Since its invention, the BS formula has been widely used by traders to determine the price for an option. However, this famous formula has been questioned after the 1987 crash. Following the Black-Scholes option pricing model in 1973, a number of other popular approaches were developed, including Cox-Ross-Rubinstein (1979) binomial tree model, Jump Diffusion model suggested by Merton (1976), the numerical method of Monte-Carlo Simulation and Finite Differences to price the derivative governed by solving the underlying PDE (Partial Differential Equation), these framework that would reflect the option market to a greater content.

The complexity of option pricing formulas and the demand of speed in financial trading market require fast ways to process these calculations; as a result, the development of computational methods for option pricing models can be the only solution. Even in the 1970s Black-Scholes calculator is a must for the option traders. As well as the option market, computing industry developed dramatically since 1970s. Computer calculation speeds is getting faster and faster, today, speculate option traders are using a selection of software applications to run the option pricing models to price the derivative, then compare the market price to looking for the mispricing opportunity to invest and act quickly to make a profit.

Options have been traded for centuries, but they remained relatively obscure financial instruments until the introduction of a listed options exchange in 1973. Since then, options trading has enjoyed an expansion unprecedented in American securities markets. Option pricing theory has a long and illustrious history, but it also underwent a revolutionary change in 1973. At that time, Fischer Black and Myron Scholes presented the first completely satisfactory equilibrium option pricing model. In the same year, Robert Merton extended their model in several important ways. These path-breaking articles have formed the basis for many subsequent academic studies.

As these studies have shown, option pricing theory is relevant to almost every area of finance. For example, virtually all corporate securities can be interpreted as portfolios of puts and calls on the assets of the firm. Indeed, the theory applies to a very general class of economic problems, the valuation of contracts where the outcome to each party depends on a quantifiable uncertain future event. It has been found that option values need not depend on the present stock price alone. In some cases, formal dependence on the entire series of past values of the stock price and other variables can be summarized using a small number of state variables. In some instances, it is possible to value options by arbitrage when this condition does not hold by using additional assets in the hedging portfolio. The value of the option then in general depend on the values of these other assets, although in certain cases only parameters describing their movement will be required. Merton's (1976) model, with both a continuous and jump components, is a good example of a stock price process for which no exact option pricing formula is obtainable purely from arbitrage considerations. To obtain an exact formula, it is necessary to impose restrictions on the stochastic movements of other securities, as Merton did, or on investor preferences. For example, Rubinstein (1976) has been able to derive the Black-Scholes option pricing formula, under circumstances that do not admit arbitrage, by suitably restricting Investor preferences. Additional problems arose when interest rates were stochastic, although Merton (1973) has shown that some arbitrage results may still be obtained.

Cox, Ross and Rubenstein (1979) derived the tree methods of pricing options, based on risk-neutral valuation, the binomial option pricing model pricing European option prices under various alternatives, including the absolute diffusion, pure-jump, and square root constant elasticity of variance models.

1.2 Statement of the Problem

Option pricing has been studied extensively in both the academic and trading context. Many approaches have been taken in the studies ranging from sophisticated general equilibrium models to ad hoc statistical fits. For the reason that options are specialized and relatively unimportant financial securities, the time devoted to the advancement and development of the pricing theory is questionable to some extent. But one justification is that, since the option is a particularly simple type of contingent claim asset, a theory of option pricing may lead to a general theory of contingent-claims pricing.

In Kenya, studies have previously been undertaken around the area of currency options with some success. Weke (2008) looks at the consequences of introducing heteroscedasticity in option pricing. His analysis showed that introducing heteroscedasticity results in a better fitting of the empirical distribution of foreign exchange rates than in the Brownian model. In the Black-Scholes world the assumption is that the variance is constant, which is definitely not the case when looking at financial time series data. In his study, he priced a European call option under a GARCH model Framework using the Locally Risk Neutral Valuation Relationship. Option prices for different spot prices were calculated using simulations. He used the non-linearity in mean GARCH model in analyzing the Kenyan foreign exchange market. He further compared the classical Black-Scholes model and the GARCH option pricing model for currency options. In his research, he recommended use of other stochastic volatility models or other statistical models to investigate the dynamics of exchange rate returns. He recommended that further research need to look at modelling exchange rates when they follow a jump-diffusion process to look into cases where the market experiences jumps at various stages.

Olweny (2011) studied the Volatility of Short-term Interest Rates in Kenya. His key findings revealed that there exists a link between the level of short-term interest rates and volatility of interest rates in Kenya. Secondly, the study's key findings revealed that the GARCH model is better suited for modeling volatility of short-term interest rates in Kenya, as opposed to ARCH models. The study further establishes that GARCH models are able to capture the very important volatility clustering phenomena that has been documented in many financial time series, including short-term interest rates. The study recommends future research to examine if other forms of the GARCH process can produce similar results (i.e., EGARCH, PGARCH, GARCH, and FIGARCH).

Aloo (2011) studied the conditions necessary for the existence of a currency options market in Kenya. His study analyzed the conditions necessary for the operation of currency options by reviewing the available literatures. He concluded that the main conditions for an option market to exist were a growing economy, supported by the central bank of Kenya, a fairly independent exchange rate mechanism, market liquidity and efficiency, a regulatory organization and a strong and developing banking system.

In this study, the application will offer a different outlook on the performance of stock pricing since it will seek to motivate more research work on pricing of the stocks and advancement of computational finance. Many studies has challenged the validity of Black-Scholes model using the empirical test which were based on the historical data set, this motivated me to produce an application to apply the real-time market data to apply for the Black-Scholes model, then compare the output price with the market stock price quote at that time point.

1.3 Objectives of the study

1.3.1 The main objective of the study

To empirically test alternative pricing models.

1.3.2 Specific objective of the study

1. To test the accuracy of the stochastic pricing models against the market stock prices.
2. To find a best moment to sell the options using the ARCH framework.

1.4 Significance of the study

This study aims at playing a major role and financial sense to several groups in the financial markets sector and they include the Nairobi Securities Exchange (NSE), Capital Markets Authority (CMA), Investment promotion agents and lastly the scholars and academicians. First, the NSE, will be the greatest beneficiary because stock market attracts more public attention than other financial markets, such as bond or commodity, the popularity could to a significant extent impact positively on the economy of the emerging markets. Second, CMA will find a tool of obtaining relevant parameters from both the stock and option market. The third group, Investment promotion centres, will be equipped with fast hand information which the general public may find very useful on making investment decisions. Lastly, Scholars and academicians from most Institutions of higher learning and other education institutes will have a privilege to extend the role in advancement option pricing and development of option trading platform.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this study, this chapter explicates the literature review and it is organized as follows. Section one introduces the research, section two reviews theories and sets out notation and assumptions. Section three reviews the empirical studies, In Section four, some discussion analyses of alternative option pricing models and distributional assumptions are imposed. Section five discusses the various empirical tests and lastly, Section six concludes.

2.2 Review of Theories

2.2.1 Stochastic Volatility

Since Black-Scholes model was introduced in 1973, many have tested it against the option miss-pricing. The correctness of generated price of BS is very depended on the accuracy of the parameter inputs. Parameter like time, exercise and strike price and interest rate are known precisely, so they are easily determined and relatively accurate. Other input, the volatility is problematic, it is difficult to precisely determine. To avoid the use of independent volatility eliminator, the implied volatility was often used, historical option market price was applied then calculated back using BS to gives the implied volatility. Consider the fact that the historical volatility is often been used as an input on BS when it actually requires the exact future volatility. Historical volatility may provide an acceptable estimate of the future, but, it is not always exact. Sometimes the poor estimation may cause the option seriously miss priced. Black and Scholes (1973) used the data from over-the-counter options market and historical volatility data to using

BS formula to calculate the theoretical value of the chosen option, then to buy the undervalued option and sell overvalued option to test if they could make excessive returns. The study showed that in the absence of the transaction cost and the tax, significant returns can be made.

Chiras and Manaster(1978) studied the data from CBOE. They found a weighted implied volatility from options on a stock at a point in time provide a much better forecast of the volatility of the stock price during the life of the option than the volatility calculated from historical data. They also tested the market to buy options with low implied volatilities and sell option with high volatilities; the strategy was successful and showed a profit of 10 percent per month, this study showed a good support of Black-Scholes model.

Rubinstein (1994) points out that if all options on the same underlying security with the same time-to-expiration but with different strike prices should have the same implied volatility. He carried out an empirical test on the S&P500 index options from 1986 to 1992 using Black-Scholes formula and the results were statistically measured in minimax percentage errors for S&P 500 index calls with time-to-expiration of 125 to 215 days. The results showed Black Scholes miss pricing is increased each year, the error was significant, furthermore, low strike price option has significantly higher implied volatilities than high striking price options. Based on his empirical test results, Rubinstein (1994) argued that the Black-Scholes model is true, but the market was inefficient. The constant volatility Black-Scholes model will fail under any of the following four violations of its assumptions: First, the local volatility of the underlying asset, the riskless interest rate, or the asset payout rate is a function of the concurrent underlying asset price or time. Secondly, the local volatility of the underlying asset, the riskless interest rate, or the asset payout rate is a function of the prior path of the underlying asset price. Third, the local volatility of the underlying asset, the riskless interest rate, or the asset payout rate is a function of a state-variable which is not the concurrent underlying asset price or the prior path of the underlying asset price; or the underlying asset price, interest rate or payout rate can experience jumps in level between successive opportunities to trade. Finally, the market has imperfections such as significant transactions costs, restrictions on short selling, taxes, non-competitive pricing, etc. It is assumed in the BS model that the underlying security pays no cash distributions, that there are no transaction costs in buying or selling the option or underlying security, that there are no taxes and there are no restriction on short sale.(Black and Scholes, 1973),

Furthermore, Wilmott et al, 1995 also summarised the assumptions for the BS: The underlying asset price follows a lognormal random walk; The risk-free interest rate r is known functions of time over the life of the option. The risk free rate is constant over time; The asset volatility v is known and not stochastic; There are no taxes, no transaction costs; No dividends payment on the underlying asset during the life of the option; Trading of the underlying asset can take place continuously and short selling is permitted and the assets are divisible; Financial markets are efficient. There are no riskless arbitrage possibilities.

Bakshi et al. (1997) conduct a much comprehensive empirical study on the pricing and hedging performance of various alternative models for S&P 500 index options. The models they test include the Black-Scholes model, the stochastic volatility model, the stochastic and jump model and the stochastic volatility and stochastic interest rate model.

The Black-Scholes pricing formula was originally developed neither by taking the limit as $n \to \infty$ of the binomial model nor by determining the expectation of option price at expiration under the assumption that stock prices are log-normally distributed at that time. Instead, it was developed from a no-arbitrage argument. Nevertheless, the Black-Scholes formula is a direct solution for the simple binomial option price as $n \to \infty$ and for the valuation based on expectation at expiration, given an underlying stock having a log-normal distribution of terminal prices.

2.2.2 Option Pricing Model

Black Scholes model states that market prices of call options tend to differ in certain systematic ways from the values given by the BS model for options with less than three months to expiration and for options that are either deep in or deep out of the money. Macbeth and Merville (1979) implied in their analysis that the BS model predicted prices were on average less than market prices for in the money options. With the exception that out of the money options with less than 90 days to expiration, the extent to which the BS model underpriced an in the money option increased with the extent to which the option was in the money and decreased as the time to expiration decreased. Furthermore, the BS model prices of out of the money options with less than 90 days to expiration were, on average, greater than market prices, but there did not appear to be any consistent relationship between the extent to which these options are overpriced by the BS model and the degree to which the options were out of the money or time to expiration.

2.2.3 ARCH Models

Autoregressive Conditional Heteroscedasticity (ARCH) models for volatility are a type of deterministic-volatility specification that makes use of information on past prices to update the current asset volatility and have the potential to improve on the Black-Scholes pricing biases. The term autoregressive in ARCH refers to the element of persistence in the modeled volatility, and the term conditional heteroscedasticity describes the presumed dependence of current volatility on the level of volatility realized in the past. ARCH models provide a well established quantitative method for estimating and updating volatility. ARCH models were introduced by Robert F. Engle (1982) for general statistical time-series modeling. An ARCH model makes the variance that will prevail one step ahead of the current time a weighted average of past squared asset returns, instead of equally weighted squared returns, as is done typically to compute variance. ARCH places greater weight on more recent squared returns than on more distant squared returns; consequently, ARCH models are able to capture volatility clustering, which refers to the observed tendency of high-volatility or low-volatility periods to group together. For example, several consecutive abnormally large return shocks in the current period will immediately raise volatility and keep it elevated in succeeding periods, depending on how persistent the shocks are estimated to be. Assuming no further large shocks, the cluster of shocks will have a diminishing impact as time progresses because more distant past shocks get less weight in the determination of current volatility. Some technical features of ARCH models also make them attractive compared with many other types of option pricing models that allow for time-varying volatility. In an ARCH model, the variance is driven by a function of the same random variable that determines the evolution of the returns. In other words, the random source that affects the statistical behaviour of returns and volatility through time is the same.

2.3 Review of Empirical Studies

A number of empirical tests on the performances of option pricing models have been conducted in recent years including Bakshi et al. (1997), evidences that alternative models perform better than the Black-Scholes formula, although relative performances of those models are different. Most of the works so far have been focusing on the model's out-of-sample performance in the following way: Parameters of the model under consideration are estimated such that the model prices for some European options match those prices that are observed in the market (e.g., from market transactions or broker quotes) at a specific time. The resulting models are then used to price some other European or American options at a later time. These model prices are then compare with the prices observed from the market at this time.

Bates (1996) has tested the performance of the Black-Scholes model, the deterministic volatility function model, and the stochastic volatility and jump model using currency options. Empirical findings suggest that option pricing is not sensitive to the assumption of a constant interest rate. For example, Bakshi et al. (1997) found that incorporating stochastic interest rates does not significantly improve the performance of the model with constant interest rates.

Corrado and Su (1998) uses the Hull and White (1988) stochastic volatility option pricing formula to study the stochastic process for the S&P 500 index implied by S&P 500 index (SPX) options. It is found that a stochastic volatility option pricing formula provides a significant improvement over a constant volatility option pricing formula. This study contributes to the empirical options literature in at least two ways. First, it provides extensive evidence that observed option prices on the S&P 500 index correspond to a mean-reverting stochastic volatility process, where return volatility is strongly negatively correlated with changes in stock index levels. Second, it shows that the parameters of a stochastic volatility process can be estimated from option prices and used to produce reliable predictions of day-ahead relationships between option prices and index levels. This represents a significant generalization of the common procedure of estimating an implied volatility from option prices.

Weke (2008) looked at the consequences of introducing heteroscedasticity in option pricing. He showed that introducing heteroscedasticity results in a better fitting of the empirical distribution of foreign exchange rates than in the Brownian model. In the Black-Scholes world the assumption is that the variance is constant, which is definitely not the case when looking at financial time series data. He priced a European call option under a GARCH model Framework using the locally risk neutral valuation relationship. Option prices for different spot prices were calculated using simulations. He used the non-linearity in mean Garch model in analyzing the Kenyan foreign exchange market.

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2.4 Alternative Option Pricing Models

There are several alternative models to the Black-Scholes model for the dynamics of an asset price. The models often have desirable properties that the Black-Scholes model lack, but are also more mathematically complex.

2.4.1 Lèvy Models

A very wide class of asset price models are models based on Lèvy processes. Lèvy processes are stochastic processes with independent, identically distributed increments. The class incorporate the Gaussian processes, as well as point processes, for example the Poisson process. The processes are characterized by their so called Lèvy triplet (μ, σ and υ). Here, μ controls the drift of the process, $\boldsymbol{\sigma}$ is connected to the Gaussian component of the process. Further, $\boldsymbol{\upsilon}$ is called the Lèvy measure, controlling the frequency and size of the jump discontinuities of the process trajectory. Models based on general Lèvy processes can be tailored to provide a better fit to empirical data than models restricted to Gaussian driving noise. It is possible to capture traits like skewness, kurtosis and fat tails in the marginal distribution.

2.4.2 Jump-Diffusion Models

A less advanced improvement over the Black-Scholes framework, using discontinuities in the asset price trajectories, are the so called Jump-Diffusion models. Originating from Merton (1976), these models are essentially continuous diffusions with an added point process component. The stochastic differential equation for a one-dimensional jump-diffusion process is typically of the following form

$$dS_t = \mu(S)dt + \sigma(S)dW_t + JdN \qquad 2.1$$

Here, J is a random variable controlling the size of the jumps and N is a Poisson process with constant intensity. In addition to the ability to incorporate instant boundary crossings, the jump component allows the model to exhibit heavy tailed marginal distributions. To be able to construct a unique replicating portfolio, the agent must be able to trade in one distinct security per possible jump size, in addition to the stock and money market account. If J is drawn from a continuous probability distribution, infinitely many new securities must be incorporated into the model. This is not consistent with real markets.

2.4.3 Stochastic Volatility Models

A stochastic volatility (SV) model can be seen as a special case of the jump-diffusion model with no jump. A general SV model takes the following form:

$$dS_t = \mu(S)dt + f(V_t)S_t dW_t^{(1)}$$

$$dV_t = g(V_t)dt + h(V_t)dW_t^{(2)} \qquad 2.2$$

where the two Brownian motions are correlated with correlation ρ, or, more formally:

$$[dW_t^{(1)}, dW_t^{(2)}] = \rho dt$$

where $[X, Y]$ denotes the quadratic covariation between X and Y . Empirical evidence seem to suggest a non zero, negative, correlation ρ. Several forms for the functions $f(x)$, $g(x)$ and $h(x)$ have been suggested. Here, we assume a constant stock-return μ. This assumption can of course be relaxed. Three stochastic volatility models are presented below.

2.4.3.1 Hull & White Model

Hull and White (1987) suggested a geometric Brownian motion for the volatility process, yielding the following model:

$$dS_t = \mu S_t dt + \sqrt{V_t}\, S_t dW_t^{(1)}$$

$$dV_t = \phi V_t dt + \varsigma V_t dW_t^{(2)} \qquad 2.3$$

A closed form solution for the European call option can be derived in the special case with zero correlation. This model for V_t has the advantage of always being positive.

2.4.3.2 Stein & Stein Model

Stein and Stein (1991) modelled the process V_t by a Ornstein-Uhlenbeck (OU) process:

$$dS_t = \mu S_t dt + |V_t| S_t dW_t^{(1)}$$

$$dV_t = \alpha(\omega - V_t)dt + \beta dW_t^{(2)} \qquad 2.4$$

The process V_t is mean-reverting with ω being the long term mean, which is a feature suggested by empirical evidence. It can, however, take on negative values. Stein and Stein solved this problem by using $f(y) = |y|$. The authors provided a closed form solution for the price of a European call in the case where $\rho = 0$. The OU process has been used by other authors as well, Scott (1987) for example used the same dynamics of V_t, but with $f(y) = e^y$.

2.4.3.2 Heston Model

In the Heston (1993) model, the driving volatility process V_t follows a CIR process. The CIR process was introduced as a model of the short rate by Cox, Ingersoll and Ross.

$$dS_t = \mu S_t dt + \sqrt{V_t}\, S_t dW_t^{(1)}$$

$$dV_t = \kappa(\theta - V_t)dt + \eta\sqrt{V_t}dW_t^{(2)} \quad 2.5$$

The Heston model is widely used, probably much due to the fact that a closed form solution exists for the European call option, regardless of the correlation ρ. We note that the process V_t can be shown to be strictly positive when $2\kappa\theta \geq \eta^2$ and nonnegative when $0 \leq 2\kappa\theta < \eta^2$.

2.5 Empirical Tests of Option Pricing Models

Some previous studies have also looked at foreign currency option pricing. Feiger and Jacquillat (1979) attempt to obtain foreign currency option prices by first pricing a currency option bond. They are not able, however, to obtain simple, closed-form solutions by this procedure. Stulz (1982) looks also at currency option bond pricing, but his paper is primarily concerned with the question of default risk on part of a contract, and it is not easy to grasp the fundamentals of foreign currency option pricing in the context of his more general investigation. Black (1976) examines commodity options, and although his results have some relevance if interest rates are non-stochastic, they are not suitably general when the primary focus is foreign currency options.

The early univariate diffusion alternatives to geometric Brownian motion were attempting to capture time-varying volatility and the "leverage" effects of Black (1976) in a simple fashion. The more recent implied binomial trees models, by contrast, were designed to exactly match observed cross-sectional option pricing patterns at any given instant, primarily in order to price over-the-counter exotic options. An exact fit is achieved by a large number of free instantaneous volatility parameters at the various nodes. One of the strengths of the approach, only asset price risk implying no-arbitrage option pricing, is also one of its major weaknesses. First, as noted by Bakshi et al. (2000), instantaneous option price evolution is not fully captured by underlying asset price movements, precluding the riskless hedging predicted by these models. Second, these models imply conditional distributions depend upon the level of the underlying asset price, which in turn counterfactually implies nonstationary objective and risk-neutral conditional distributions for stock, stock index, or exchange rate returns. Third, these models use time-dependent instantaneous volatilities S(t), which creates difficulties for implementing empirical tests premised on the stationarity assumption that calendar time does not matter. This last awkwardness is shared by bond pricing models that rely on time-dependent processes to exactly match an initial term structure of bond yields.

Standard jump models have primarily been used to match volatility smiles and smirks. This they can do fairly well for a single maturity, less well for multiple maturities. As discussed by Bates (2000), the standard assumption of independent and identically distributed returns in jump models implies these models converge towards BSM option prices at longer maturities in contrast to the still-pronounced volatility smiles and smirks at those maturities. The independent and identically distributed return structure is also inconsistent with time variation in implicit volatilities. Furthermore, only infrequent large jumps matter for option pricing deviations from Black-Scholes, and it is difficult to estimate such models on time series data.

The major strength of stochastic volatility models is their qualitative consistency with the stochastic but typically mean-reverting evolution of implicit standard deviations. The option pricing implications of standard stochastic volatility models are otherwise fairly close to an ad hoc Black–Scholes model with an updated volatility estimate, when the volatility process is calibrated using parameter values judged plausible given the time series properties of asset volatility or option returns. Consequently, standard stochastic volatility models with plausible parameters cannot easily match observed volatility smiles and smirks, while even unconstrained stochastic volatility models price options better after jumps are added. However, Bakshi et al. (1997) found that adding jumps or stochastic interest rates does not improve the unconstrained stochastic volatility model's assessments of how to hedge option price movements.

Since every simple option pricing model has its weaknesses, hybrid models are needed and are feasible within the affine model structure. Having jump components addresses moneyness biases, while having stochastic latent variables allows distributions to evolve stochastically over time. Furthermore, Bates (2000) finds that modelling jump intensities as stochastic alleviates the maturity-related option pricing problems of standard jump models. It is interesting that the latest binomial tree models incorporate additional stochastic components as well.

The use of hybrid models has been a mainstay of the time series literature since the t-GARCH model of Bollerslev (1987). The latest time series analyses suggest that even these models may be inadequate to describe discernable patterns in volatility evolution. Volatility assessments from intradaily returns and from high–low ranges indicate longer-lasting volatility shifts than are typically estimated in the ARCH framework, and suggest either a long-memory or a multifactor volatility process. The paper by Chernov, Gallant, Ghysels, and Tauchen (2003) examines various continuous-time specifications using a 37-year history of daily Dow Jones returns and the EMM/SNP methodology. They concluded that various diffusion-based specifications require at least a two-factor stochastic volatility model to simultaneously summarize volatility evolution and capture the fat-tailed properties of daily returns, while affine specifications require jumps in returns and/or in volatility, and probably both. Furthermore, they find evidence of substantial volatility feedback: volatility is itself more volatile at higher levels. While the analysis by Chernov et al. (2003) is not confined to affine models, they argue that the comparable fit and analytic convenience may make affine specifications preferable.

2.6 Conclusions

The main shortcoming, problem or gaps with alternative pricing models or jump-diffusion models is that they cannot capture the volatility clustering effects, which can be captured by other models such as stochastic volatility models. In summary, many alternative models may give some analytical formulae for standard European call and put options, but analytical solutions for interest rate derivatives and path-dependent options, such as perpetual American options, barrier and lookback options, are difficult, if not impossible. In the double exponential jump-diffusion model analytical solution for path-dependent options are possible. However, the jump-diffusion models cannot capture the volatility clustering effect.

Therefore, alternative pricing models are more suitable for pricing short maturity options in which the impact of the volatility clustering effect is less pronounced. In addition jump-diffusion models can provide a useful benchmark for more complicated models, for which one perhaps has to resort to simulation and other numerical procedures. More general models combine jump-diffusions with stochastic volatilities resulting in “affine jump-diffusion models,” as in Duffie et al. (2000) which can incorporate jumps, stochastic volatility, and jumps in volatility. Both normal and double exponential jump diffusion models can be viewed as special cases of their model. However, because of the special features of the exponential distribution, the double exponential jump-diffusion model leads to analytical solutions for path-dependent options, which are difficult for other affine jump-diffusion models (even numerical methods are not easy). Furthermore, jump-diffusion models are simpler than general affine jump-diffusion models; in particular jump-diffusion model have fewer parameters that make calibration easier. Therefore, jump-diffusion models attempt to strike a balance between reality and tractability, especially for short maturity options and short term behavior of asset pricing.

A significantly number of empirical evidence in literature suggest that the Black-Scholes model, which assumes that asset returns follow a continuous diffusion process with constant conditional volatility, is inconsistent with the statistical properties of many asset prices.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the methodology that is used in this study. It commences with an overview of the research design, and then details the methods for the quantitative study in terms of target population, sampling design, procedure of data collection, statistical techniques used for data analysis. The last section explicates the validity and reliability of the data used in the study.

3.2 Research Design

This study tries to investigate the prospects of introducing empirical alternative option pricing models towards the advancement and performance of securities markets in Kenya. To conduct this study and to realize the objectives of the study, a quantitative research design is used due to its appropriateness. The research also tries to explore the prospects, opportunities, problems and challenges that face listed companies. Quantitative data were collected to examine the models. The performance measurement variables are trading pattern classifications and include the trading indicator, whether real, financial or commodity and are all defined within their context of options. The design is made appropriate by parameterizing the variables into the best line of fit and testing for minimal errors using EMM methodology.

3.3 Population

The population consists of 60 companies listed on Nairobi Securities exchange and registered with the CMA. To be specific, the sample uses the registered and listed members NSE in 2012.

3.4 Sample

The study proposes and adopts theoretically the population of 52 listed companies on NSE. The population is made up of stock exchange members licensed by the capital markets authority, which then formed the sampling frame. Data is sampled from NSE monthly reports and CMA stock data (2012) for Companies that consistently traded for a period of 12 months.

3.5 Data Collection

The study, to a major extent, relies on data collected from secondary sources, specifically, the CMA and NSE. Other sources included, but not limited to, scholarly or media publications. Quantitative data is categorized, documented and the findings presented in tabular and graphical presentations with the inclusion of analytical interpretation narratives. The data were subjected to analysis using the Statistical Packages for Social Sciences (SPSS Statistics 17.0).

3.6 Data Analysis

In this study, the data is analyzed through descriptive statistics. Multivariate analysis of the classical econometric GARCH type regression model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \qquad 3.1$$

is used for analyzing historical quantitative data from NSE volatility index.

Where;

Y is the realized volatility or observed volatility.

β_0 is the constant term.

X_1 is the log return of implied volatility of at-the-money security price on the NSE all share index measured at the beginning of the month.

X_2 is the log return of implied volatility of at-the-money security price on the NSE all share index measured at the end of the month.

X_3 is the monthly NSE all share index.

ε is the error term.

Multivariate regression analysis is a flexible method of data analysis that may be appropriate whenever a quantitative variable (the dependent or criterion variable) is to be examined in relationship to any other factors (expressed as independent or predictor variables). Relationships may be nonlinear, independent variables may be quantitative or qualitative, and one can examine the effects of a single variable or multiple variables with or without the effects of other variables taken into account. The tests of statistical significance for both standardized and unstandardized regression coefficients for a variable X_j are also identical to the tests of significance for partial and semi-partial correlations between Y and X_j if the same variables are used. This is because the null hypotheses for testing the statistical significance of each of the statistics (constant term, beta, partial correlation, and semi-partial correlation) have the same implication. The variable of interest does not make a unique contribution to the prediction of Y beyond the contribution of the other predictors in the model.

3.7 Data Validity and Reliability

As this is a causal study, conclusive validity is being considered. The methods used are applied to assess the performance of options pricing on securities markets in Kenya hence these constructs are valid. Data validity is concerned with the degree to which research findings can be applied to the real world, beyond the controlled setting of the research. This is the issue of generalisation. In this study, we shall focus on the validity and reliability of quantitative research and restrict ourselves further to the process of data collection. Validity and reliability are crucial themes in the development of a more adequate methodology for quantitative research. Specifically, this study aims at the descriptive method in computational finance. This limitation implies that alternatives are left open and that one can put different emphases in other fields of applications. To locate the aim of this study explicitly, we shall describe briefly the data collection method and its purposes. Data reliability compares the opinion from an initial test with repeated measures later on, the assumption being that if the instrument is reliable there will be close agreement over repeated tests if the variables being measured remain unchanged.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION OF FINDINGS

4.1 Introduction

This chapter explains how the data that has been used in this study is being presented. It also provides a detailed summary and interpretation of results based on the tools and software of analysis, major findings and tries to relate these findings with other previous studies already carried out on the related subject.

4.2 Data Presentation

4.2.1 Secondary Data Sources

The secondary data for this study was collected by reviewing published materials on the equity trading of stocks. The secondary research was restricted to cover the period from January 31, 2012 to December 31, 2012 to enable an up to date and relevant analysis from the data collected. The research was undertaken by reviewing published materials for example the NSE Monthly Statistical bulletins (2012) and also by using various on-line databases for example CMA Quarterly Statistical Bulletins. These published materials were obtained from both NSE and CMA. The findings of this and the other reports will be compared with that of this study in the next section.

4.2.2 The Equity Trading Summary Data

The appendices 1 to 12 are the monthly detailed Equity trading returns (January to December 2012) of the 52 sampled companies with the reported share price, share price A is the stock price at the beginning of the month, share price B is the price at the end of the month, return is the monthly growth in the share price, $\boldsymbol{\sigma_A}$ is ATM volatility measured at the beginning of the month, σ_B is ATM volatility measured at the end of the month, $\ln\sigma_A$ is the logarithmic realized volatility at the beginning of the month, $\ln\sigma_B$ is the logarithmic realized volatility at the end of the month and ASI is the NSE all share index. The data, NSE Monthly Bulletins 2012, is sourced from CMA.

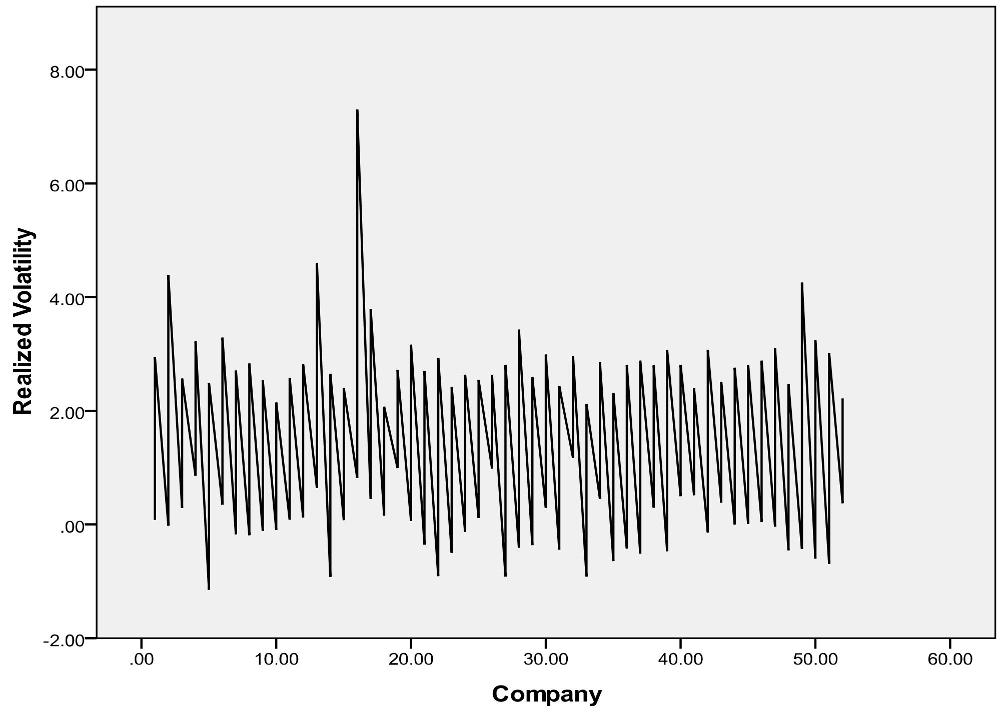

Figure 4.1: Company Logarithmic Realized Volatility graph which is the representation of the observed monthly volatilities for the 52 companies represented alpha-numerically on the x-axis.

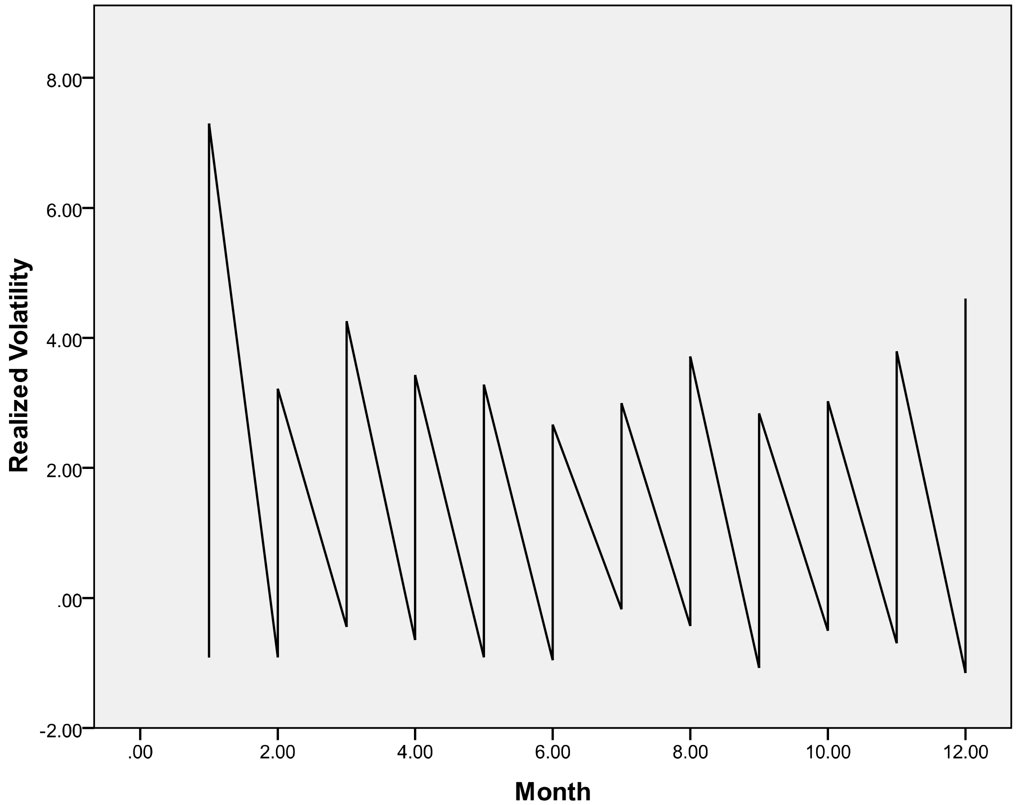

Figure 4.2: Logarithmic Realized Volatility movement during the year averaged for the 12 month period in 2012. Specifically, Month 1 is January and Month 12 is December.

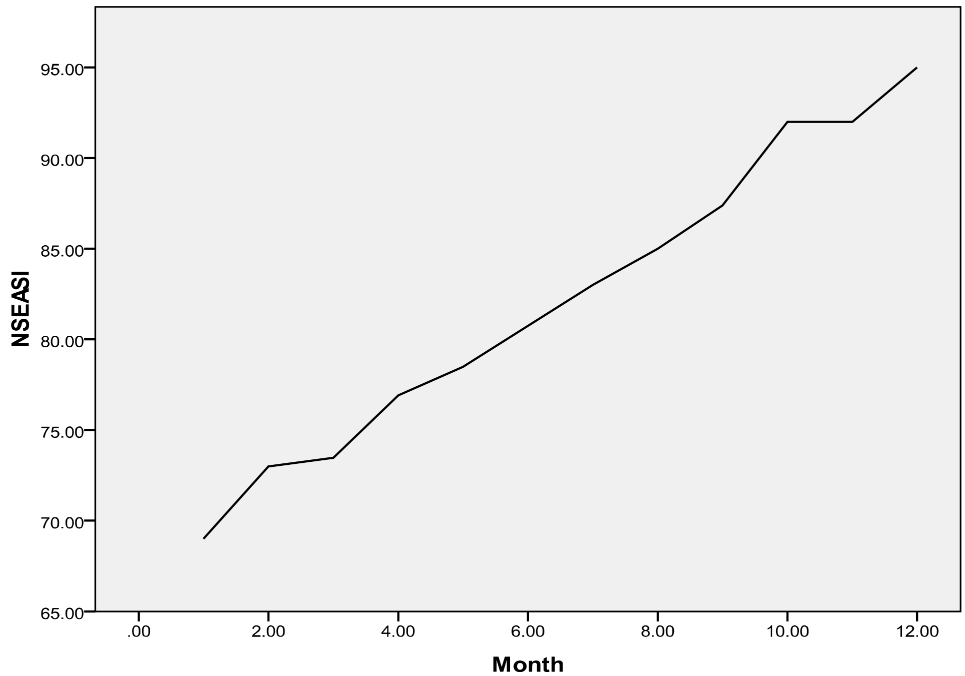

Figure 4.3: Monthly NSE ASI movement graph which indicates shows the growth of the monthly ASI during the period under study.

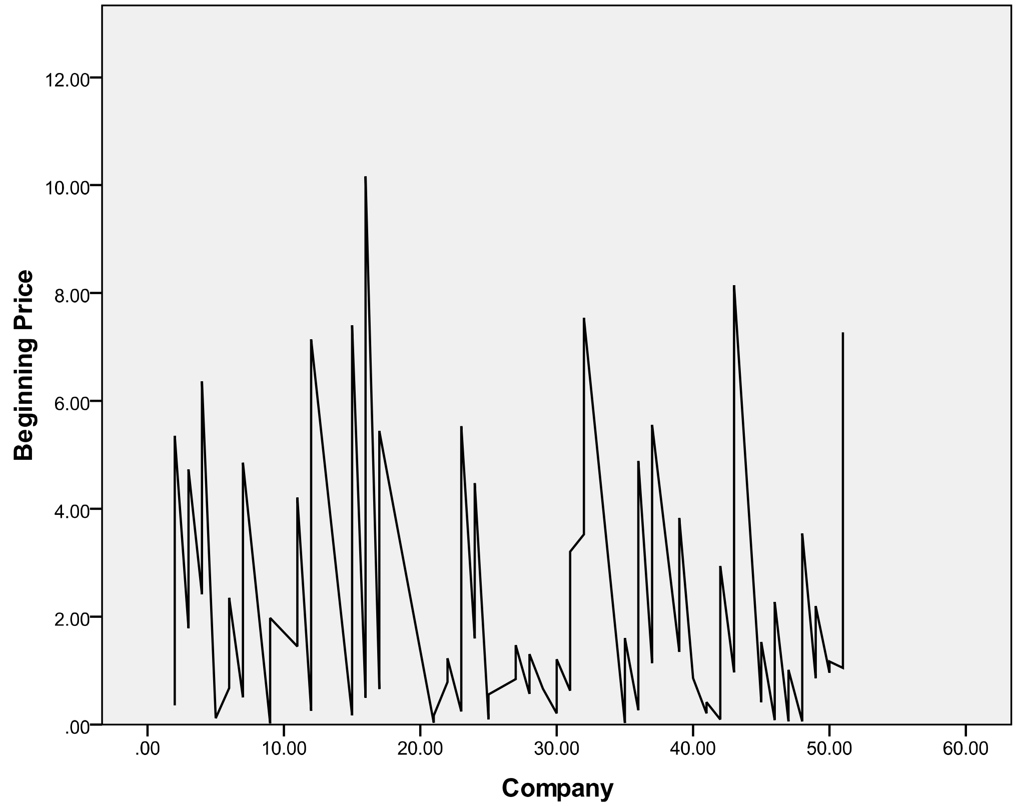

Figure 4.4: Logarithmic Share price graph determined at the beginning of each month which is the representation of the observed monthly share price at the beginning of each month for the 52 companies represented alpha-numerically on the x-axis.

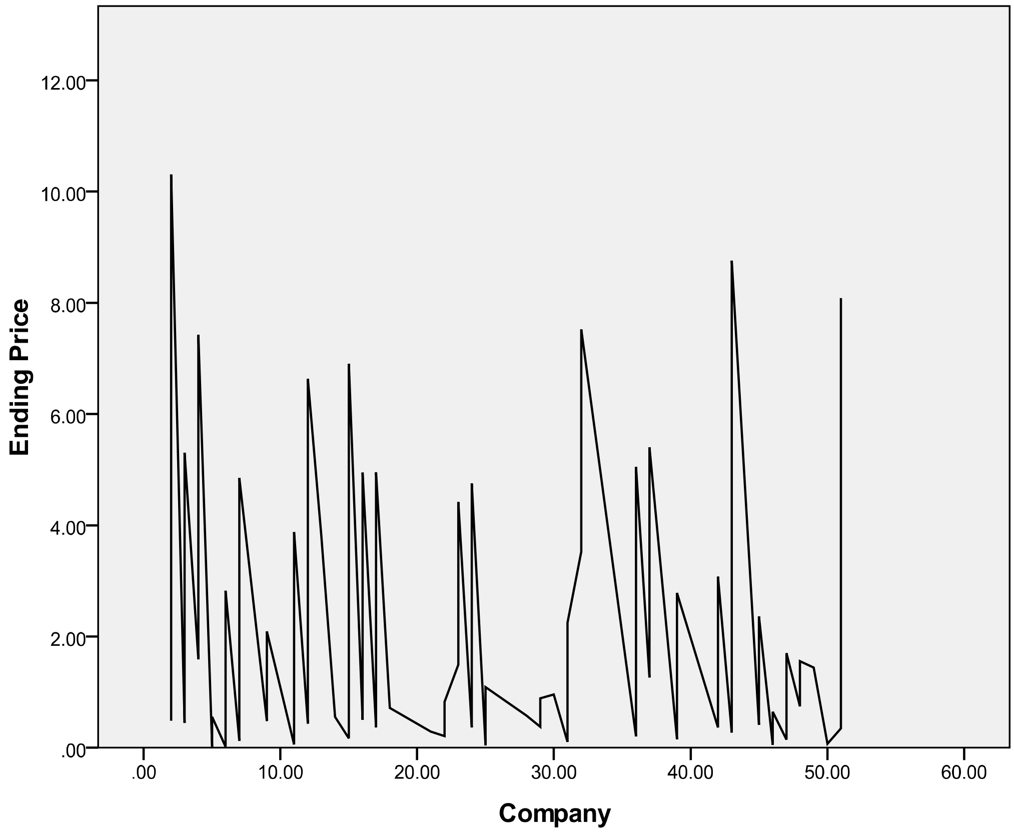

Figure 4.5: Logarithmic Share price graph determined at the end of each month which is the representation of the monthly share price at the end of each month for the 52 companies represented alpha-numerically on the x-axis.

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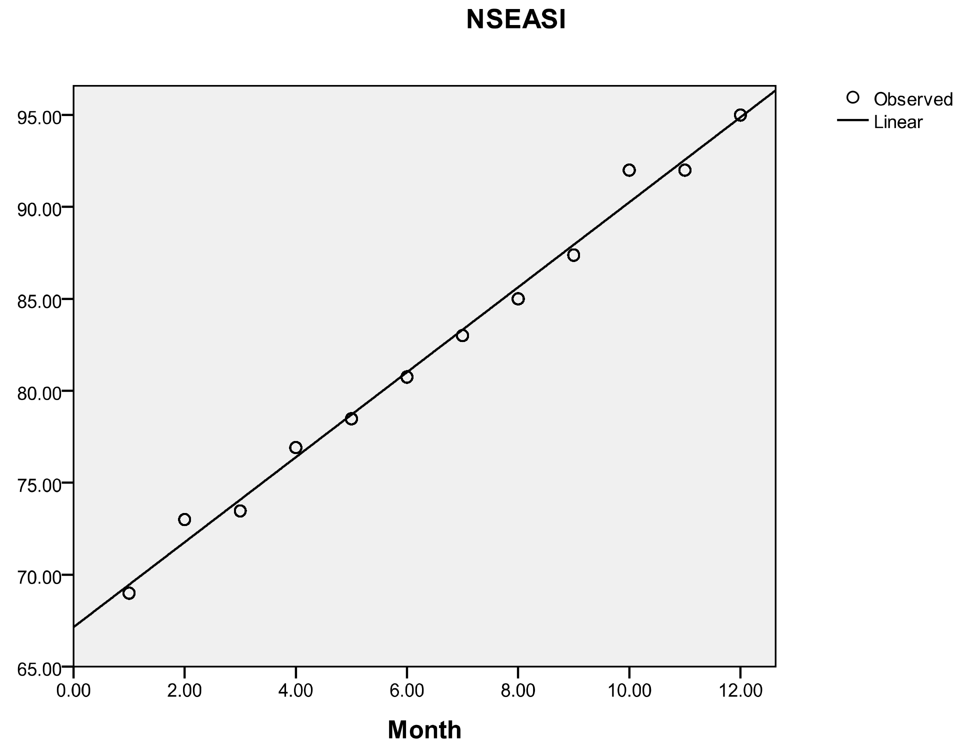

Figure 4.6: 2012 NSE all share indices movement graph. The figure represents the best line of fit of the monthly all share index.

4.2.3 Descriptive Statistics

In this study, the variables are being presented as logarithmic of results of variances of Security prices at the beginning and end of each month. Realized volatility is the natural logarithm computed on the absolute percentage of return on the monthly security price. The NSE All Share Index (NSEAI) is a fixed variable.

Table 4.1 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Company	624	1.00	52.00	26.500	15.02037
NSEASI	624	69.00	95.00	82.165	8.01807
Month	624	1.00	12.00	6.5000	3.45482
Beginning Price	240	.02	10.16	2.5539	1.89503
Ending Price	215	.02	10.31	2.5895	1.94479
Realized Volatility	564	-1.15	7.30	1.5468	.97098
Valid N (listwise)	146				

4.2.4 Statistical Regression Model

The models are estimated using monthly NSE All Share index returns and monthly implied volatilities from the NSE equity market. The time period considered extends from January 31, 2012 to December 31, 2012, a sample size of 624 observations. The NSE All Share index was chosen over the NSE 20 Share index partly because the NSE All Share index's more liquid equity market during the year. The more compelling reason to analyze the NSE All Share index, however, is the availability of the NSE Market Volatility Index.

4.2.5 Results

Table 4.2: Correlations

		Realized Volatility	Month	Beginning Price	Ending Price	NSE ASI
Pearson Correlation	Realized Volatility	1.000	-.185	.395	.251	-.179
	Month	-.185	1.000	-.005	.017	.995
	Beginning Price	.395	-.005	1.000	.525	.000
	Ending Price	.251	.017	.525	1.000	.029
	NSEASI	-.179	.995	.000	.029	1.000
Sig. (1-tailed)	Realized Volatility	.	.013	.000	.001	.015
	Month	.013	.	.477	.418	.000
	Beginning Price	.000	.477	.	.000	.496
	Ending Price	.001	.418	.000	.	.363
	NSEASI	.015	.000	.496	.363	.
N	Realized Volatility	146	146	146	146	146
	Month	146	146	146	146	146
	Beginning Price	146	146	146	146	146
	Ending Price	146	146	146	146	146
	NSEASI	146	146	146	146	146

Table 4.3: Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	NSEASI, Beginning Price, Ending Price[a]	.	Enter

a. All requested variables entered.

Table 4.4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.438[a]	.192	.175	.96576

a. Predictors: (Constant), NSEASI, Beginning Price, Ending Price

Table 4.5: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.078	.843		3.651	.000
	Beginning Price	.195	.048	.360	4.062	.000
	Ending Price	.035	.047	.067	.756	.451
	NSEASI	-.024	.010	-.181	-2.396	.018

a. Dependent Variable: Realized Volatility

Table 4.6: ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.390	3	10.463	11.218	.000[a]
	Residual	132.442	142	.933		
	Total	163.832	145			

a. Predictors: (Constant), NSEASI, Beginning Price, Ending Price

b. Dependent Variable: Realized Volatility

Table 4.7: Coefficient Correlations[a]

Model			NSEASI	Beginning Price	Ending Price
1	Correlations	NSEASI	1.000	.019	-.035
		Beginning Price	.019	1.000	-.525
		Ending Price	-.035	-.525	1.000
	Covariances	NSEASI	.000	9.260E-6	-1.644E-5
		Beginning Price	9.260E-6	.002	-.001
		Ending Price	-1.644E-5	-.001	.002

a. Dependent Variable: Realized Volatility

Table 4.8: Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.7627	3.4931	1.8059	.46656	146
Residual	-2.45977	3.80231	.00000	.95509	146
Std. Predicted Value	-2.236	3.616	.000	1.000	146
Std. Residual	-2.540	3.926	.000	.986	146

a. Dependent Variable: Realized Volatility

Table 4.9: Multivariate Tests[b,c]

Effect		Value	F	Hypothesis df	Error d.f	Sig.
Intercept	Pillai's Trace	.144	11.855[a]	2.000	141.000	.000
	Wilks' Lambda	.856	11.855[a]	2.000	141.000	.000
	Hotelling's Trace	.168	11.855[a]	2.000	141.000	.000
	Roy's Largest Root	.168	11.855[a]	2.000	141.000	.000
Price1	Pillai's Trace	.054	3.988[a]	2.000	141.000	.021
	Wilks' Lambda	.946	3.988[a]	2.000	141.000	.021
	Hotelling's Trace	.057	3.988[a]	2.000	141.000	.021
	Roy's Largest Root	.057	3.988[a]	2.000	141.000	.021
Price2	Pillai's Trace	.021	1.538[a]	2.000	141.000	.218
	Wilks' Lambda	.979	1.538[a]	2.000	141.000	.218
	Hotelling's Trace	.022	1.538[a]	2.000	141.000	.218
	Roy's Largest Root	.022	1.538[a]	2.000	141.000	.218
NSEASI	Pillai's Trace	.061	4.607[a]	2.000	141.000	.012
	Wilks' Lambda	.939	4.607[a]	2.000	141.000	.012
	Hotelling's Trace	.065	4.607[a]	2.000	141.000	.012
	Roy's Largest Root	.065	4.607[a]	2.000	141.000	.012

a. Exact statistic

b. Design: Intercept + Price1 + Price2 + NSE ASI

c. Weighted Least Squares Regression - Weighted by Month

Table 4.10: Tests of Between-Subjects Effects[c]

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Realized Volatility	137.652[a]	3	45.884	8.193	.000
	Company	12331.048[b]	3	4110.349	2.570	.057
Intercept	Realized Volatility	45.219	1	45.219	8.074	.005
	Company	24269.633	1	24269.633	15.174	.000
Price1	Realized Volatility	44.865	1	44.865	8.011	.005
	Company	8.394	1	8.394	.005	.942
Price2	Realized Volatility	10.470	1	10.470	1.869	.174
	Company	2100.104	1	2100.104	1.313	.254
NSEASI	Realized Volatility	17.510	1	17.510	3.126	.079
	Company	9451.467	1	9451.467	5.909	.016
Error	Realized Volatility	795.295	142	5.601		
	Company	227110.698	142	1599.371		
Total	Realized Volatility	3673.208	146			
	Company	701456.000	146			
Corrected Total	Realized Volatility	932.947	145			
	Company	239441.746	145			

a. R Squared = .148 (Adjusted R Squared = .130)

b. R Squared = .051 (Adjusted R Squared = .031)

c. Weighted Least Squares Regression - Weighted by Month

The independent variables included are the log of variance of share price at the beginning of the month ($\boldsymbol{\sigma_A}$), the log of the variance of share price at the end of the month ($\boldsymbol{\sigma_B}$), and the Monthly NSE All Share Index. The Realized Volatility, Y, is a dependent variable, vector of dummy variables, obtained by combining log of real returns of stocks from the list of companies on CMA. This functional form is used because its Box-Cox transformation gives the highest log likelihood, lowest standard error, and highest R Squared. From these equations we estimate the coefficients to be used to determine the volatility value on a stock. The results from each of these regressions are presented in

Tables 4.2 to 4.5. The fit of the regressions is good for all equities during the year, with R squared ranging from 0.051 to 0.148.

4.3 Summary and Interpretation of Findings

Findings are presented in tabular and graphical presentations with the inclusion of analytical interpretation narratives. The analysis is based on evidence from 52 local companies which traded actively on NSE representing 86.66% of the total population of the population of NSE. Appendices 1 to 12 show that equity trading return indicators of stock market development via trading activity measures are small implying that most stock markets are, therefore, characterized by low provision of liquidity. Table 4.2 shows and summarizes empirical results obtained using the volatility adjusted security price regression model. Price data used here are the data from appendices 1 to 12. Only these monthly lagged parameter estimates are used to calculate theoretical security prices. Therefore, the empirical results reported in Table 4.2 are based on ATM sample parameter estimates.

The result obtained from the estimation output of SPSS Statistics 17.0 for the empirical model at its transformed variables form is presented in table 4.5. The specified model formulated to capture the realized volatility is given as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

The estimated model based on the result presented in table 4.5 is given as:

$$Y = 3.078 + 0.195 \ln\sigma_A + 0.035 \ln\sigma_B - 0.024 \text{NSEASI} + \varepsilon$$

In order to estimate at-the-money dependent volatility in the regression model historical prices for 12 months of the year were used. Such time interval is required to ensure that prices of all three types (out-of-the-money, at-the-money and in-the-money) are present in the historical sample and average implied volatilities in each class can be calculated. The summary statistics for averaged implied volatilities estimates is provided in the Table 4.4.

From the Multivariate tests of dependent variables in Table 4.9, the positive null hypothesis will for the transformed parameter estimates for security price measured ATM at the beginning of the month, at the end of the month at α=0.021 and α=0.218 level of significance respectively. From these level of significance, it can be concluded whether trading activity in equities have any stabilizing or destabilizing effects on the underlying volatility, and how big the behavioural finance element in the pricing process is. Also, we will not touch upon Implied Volatilities due to its relation to option pricing models, which are distinctive, different from both Stochastic Volatility Models and GARCH models.

The major findings in this study have evidenced that positive correlation between stock index returns and volatility has the following two implications. On one hand, when the stock index return is high, volatility tends to be high. Conversely, when the stock index return is low, volatility tends to be low. This yields a symmetric distribution of returns where a large negative return is significantly less likely to occur than a large positive return. Thus, compared to a stochastic volatility specification with a negative correlation between index returns and volatility, this model overstates the likelihood of a large upward move in the NSE all share index and understates the likelihood of a small downward move.

Furthermore, any model should be able to capture some important empirical phenomena. However, empirical tests should not be used as the only criterion to judge a model good or bad. Empirical tests tend to favour models with more parameters. However, models with many parameters tend to make calibration more difficult (the calibration may involve high-dimensional numerical optimization with many local optima), and tend to have less tractability. This is a part of the reason why scholars still like the simplicity of the Black–Scholes model. The empirical tests performed in Ramezani and Zeng (2002) suggest that the double exponential jump diffusion model fits stock data better than the normal jump-diffusion model, and both of them fit the data better than the classical geometric Brownian motion model.

This study can be compared to the Corrado and Su (1998) which explored the stochastic volatility process for the Standard and Poor's 500 index implied by S&P 500 index (SPX) option prices. The major tool for their analysis was the stochastic volatility option pricing formula derived by Hull and White (1988).

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

This study explores and characterizes the methodology that is currently employed for the construction of volatility indices in equity markets around the world, and summarizes some of their applications and documented stylized facts by reviewing the up-to-date literature on volatility indices.

This study has presented a new pricing approach and examines the volatility index by using GARCH-type approximation relation on a security in a local capital market. The originality of this approach is to model the local volatility of the securities to obtain accurate approximations with tight estimates of the error terms. This approach can also be used in the case of pricing options with stochastic convenience yields. The model is applied to Nairobi Securities Exchange (NSE) All Share Index Stock data. From the real market data, the realized volatility is empirically analysed by measuring the deviations of pricing errors. Because of its analytical tractability, the implied parameters are estimated from minimizing the weighted sum of squared errors between the market data.

Research on volatility indices and the increasing number of these studies leave room for new lines of future research. Examining in depth the role of volatility indices as investors measure of fear in foreign markets extends the evidence on volatility spillovers between continents, and constructs volatility indices over longer forecast horizons so as to estimate volatility term structures for different markets are some directions of future research with appealing implications for portfolio managers.

5.2 Conclusions

Emanating from the study findings, it can be deduced that external shock and other macroeconomic variables dictates the movement of stock market prices performance and volatility, and some of these key variables are the significant determinants of the stock market performance in Kenya during the reviewed period. Specifically, the changes in exchange rate of Kenya Shilling vis-à-vis Sterling Pound and interest rate were found to exert significant impact on the growth of the NSE all share index in 2012.

This study empirically investigates the stochastic behavior of monthly stock market returns and the relationship between market data returns and volatility for Kenya stock indices. This paper applied the GARCH-type statistical regression model with slight modifications to account for the deviations of pricing errors. The stock returns have serial correlation in their squared return series. That is, the presence of conditional heteroskedasticity or volatility clustering. The mean equation results show serial correlation in the return series for Kenya exchange in violation to the martingale model of stock prices. That is, there is a significant first moment dependency of stock returns. On the other hand, no significant relation is found between conditional variance and expected return for Kenya stock market, but Kenya stock market is found to be vulnerable pricing errors. The stochastic behaviors of stock returns for emerging markets have important implication for market equilibrium models.

Since NSE all share index options are analysed daily, the approach of this study can be used to adjust volatility index levels by measuring deviations of pricing errors of future share prices before expiration of each trading period. Daily share prices for the NSE all share index are obtained from the NSE Information Bulletins.

5.3 Policy Recommendations

The following policy options are recommended to bring about enhanced stock market performance amidst macroeconomic fluctuations and external forces.

First, the government should review and fine tune the exchange rate policy and institute a consistent policy plan to mobilize surplus funds from foreign states, which would be injected into the capital market for significant development.

Secondly, the standard of living of the citizens as measured by Per Capital Income (PCI) should be increased by providing essential infrastructural community facilities in order to increase the ability of the people to invest in the Kenyan capital market.

Third, it is desirable for returns on equities to be inflation hedge. For Kenyan equities to have this property, this study recommends a full deregulation of the entire price formation process in the capital market.

Fourth, the government and the Nairobi Securities Exchange (NSE) should create a special fund called stabilization securities fund to stabilize the market in the presence of external shocks. This will to make the market attractive to proposed, existing and foreign investors.

Lastly, considering the level of process of the Kenyan capital market, to external shock the concerned authorities should institute policies and mechanism that will stabilize significant macroeconomic indicators in order to promote the capital market.

5.4 Limitations of the Study

In this study, the market volatility index represents an average of implied volatilities from equity market on the NSE All Share index. The use of the Volatility index could be criticized on the grounds that it is a hypothetical measure, since the index does not generally coincide with the implied volatility of any particular share price traded that month. Similar criticism could be aimed at term structure research that uses bootstrapped and interpolated values to construct constant maturity zero coupon yields. Partly because of these concerns,

In this study we allow for the possibility that the volatility index makes random deviations from the implied volatility of the hypothetical share price that it is designed to mimic. An assessment of the magnitude of this error will be an output of the estimation. This relaxation of the purely deterministic link between data from the underlying and equity markets represents a departure from previous studies that have combined data from the two markets. In theory, given the synchronous observation of the underlying asset's price and perhaps some other market fundamentals, share prices can be inverted to yield the underlying asset's exact instantaneous volatility. Relaxing the strictness of this relation reflects a purely empirical perspective and is similar to the allowance of additional error terms in term structure research, where theory implies, for example, that security yields of all maturities are deterministically linked in a single-factor term structure model. The realities of security price data, which include sources of error such as asynchronous data and bid-ask spreads, make deterministic relations as unrealistic in options.

As part of this study, further analysis of market makers' risk management issues appears warranted. There has, of course, been a substantial empirical study of option hedging under frictions such as discrete-time hedging or transactions costs, but most of that literature has been partial-equilibrium in nature, and premised on BSM assumptions of geometric Brownian motion for the underlying security price. Devising plausible models of market behaviour under more general risks and incorporating them into equilibrium models of risk pricing is desirable.

It is also possible that transaction costs may be relevant for some of the observed pricing puzzles. However, the fact that the deviations between objective and risk-neutral probability measures appear substantially more pronounced for security index options than for derivatives market suggests that such costs are not the major factor. Furthermore, those models are difficult to work with even in a geometric Brownian motion framework, and have not yielded especially useful insights. One conclusion is that it appears unproductive to combine transaction costs and the no-arbitrage foundations of BSM. Such approaches implicitly assume option market makers are infinitely risk-averse, and generate excessively broad bid-ask spreads, for example, the asking price for a an equity is the value of the underlying stock. Transaction costs models need to operate in conjunction with a more plausible risk-return calculation on the part of the equity market players.

Although this study provides the results that are relatively understandable and consistent with the previous studies on emerging capital markets, the results should be treated with caution due to the following reasons. Firstly, the data period of one year period and the number of listed companies in NSE are quite limited for applying GARCH models comparable to the empirical studies with longer time horizon of estimation. Secondly, though the study attempts to comprehensively investigate the volatility in Kenyan stock market by the means of various univariate GARCH models, it covers the most widely used models without consideration of the huge number of other GARCH extensions and other approaches such as stochastic volatility models.

These limitations suggest the further studies on the same subject to generate more fruitful results. As the Kenyan stock market increasingly develops, the data set is updated and provides more stable observations. Thus empirical results might be more decisive and reliable. Since the choice of goodness-of-fit volatility estimation and best-performing forecast models is still an interesting and open question, alternative GARCH specifications as well as other simpler or more sophisticated approaches maybe conducted to give a systematically finding of the best models.

Dumas, Fleming and Whaley (1998) acknowledge that their research assumes a null hypothesis that the volatility is an exact function of asset price and time. They also recognise that volatility may be stochastic and given the difficulty in estimation of these processes and preference free security valuation, they suggest this for further research. This research eliminates this problem by indexing all volatilities to the level of the ATM volatility. Subsequent research will examine whether stochastic volatility models are sufficient to explain the relative shapes of implied volatility surfaces.

The logarithm, rather the absolute level, was used due to the wide discrepancies in the levels of the futures for the Kenyan equity markets. Standardisation of variables is common in economic problems, when the objective is to remove impacts of scaling. As was discussed previously, we are not interested per se in the absolute level of the volatility or of the smile but of the relative relationships. This will allow for both inter-temporal comparisons within markets and allow comparisons between markets. The inclusion of the levels of the ATM volatility and the futures price will provide a check that important dynamics of the model have not been missed. The t-statistics for all the independent variables indicate whether the coefficient is statistically significantly different than zero. For the intercept, the t-statistic indicates whether the coefficient (alpha) is statistically significantly different than 100.

5.5 Suggestions for Further Studies

This study stands alone by formulating the correct questions to ask, by uncovering regularities for implied volatility surfaces, which seem to summarise the general phenomenon both within and between the equity markets on financial assets. This provides future researchers with benchmarks for the comparison of suitable models and insights into future models to be developed.

Another suggestion is that further study may employ multivariate models such as Dynamic Conditional Correlation Multivariate model to analyze the time-varying correlation of Kenyan stock market with the other African markets in particular and international markets in general. The models can be used to examine the volatility spillovers and covariances between these markets' return series. Findings of those researches may give good indications to forecast volatility of Kenyan stock market.

Finally, it is safe to predict that numerical methods will be used increasingly in future empirical options research. Computers continue to get faster at a remarkable pace, and the need for analytically tractable models diminishes as alternative brute-force methods become cheaper. An expositional barrier will still remain, however, explaining the methodology and the results given the many methods discussed above whereby option pricing models can be tested. Implementing any of the above suggestions and presenting them intelligibly is will be a major scholarly research for advancement of finance.

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