DYNAMICS OF STOCK RETURN VOLATILITY AND LEVERAGE EFFECT ON SHARE PRICE RETURNS AT THE NAIROBI SECURITIES EXCHANGE IN KENYA

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D63/71266/2014

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RESEARCH PROJECT SUBMITTED TO SCHOOL OF BUSINESS, IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF MASTERS OF SCIENCE IN FINANCE DEGREE, UNIVERSITY OF NAIROBI

AUGUST, 2015

## DECLARATION

I declare that this project is my original work and has not been presented in any other university/ institution for consideration of any certification. This research proposal has been complemented by referenced sources duly acknowledged.

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## ACKNOWLEDGEMENT

To family and friends, my constant source and encouragement, I thank you all.

## DEDICATION

This project is dedicated to my family and friends who have motivated and guided me throughout my graduate studies.

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## ARREVIATIONS

NSE- Nairobi Stock Exchange

ARCH- Autorogressive conditional heteroscedastic

E-GARCH- Exponential Autorogressive conditional heteroscedastic


#### Abstract

Stock return volatility has been a subject of interest among finance researchers and this due to the fact that volatility is that stock return volatility influences stock price movement. The study analyses the volatility in conditional stock returns at Nairobi Securities Exchange for the period $2^{\text {nd }}$ January 2010 to $31^{\text {st }}$ December 2013. The study uses the Autorogressive conditional heteroscedastic - family econometric models to test for both the stock returns volatility and leverage effect at the Nairobi Securities Exchange. More specifically, the study focused on the main aspects of daily returns with special attention on volatility clustering and the leverage effect. More specifically autorogressive conditional heteroscedastic $(1,1)$ and Exponential generalized autorogressive conditional heteroscedastic were estimated. The study used secondary data of all the daily security prices from January 2010 to December 2013 and concluded that Nairobi Securities Exchange is not a weak - form efficient market. The study also confirms that volatility clustering is evident at the Nairobi securities exchange as portrayed by the significance of the coefficients of the autorogressive conditional heteroscedastic (1) terms. Lastly leverage effect was confirmed at the Nairobi securities exchange for the period under review implying the existence of information asymmetry in the market. Therefore, the stock returns and the market volatility are negatively related meaning that in the time of high market volatility, the bearish behaviour rules the market while in the time of low volatility bullish behaviour takes an upper hand in the market.


## CHAPTER ONE

## INTRODUCTION

### 1.1 Background to the Study

Stock returns volatility has received a lot of attention especially among the researchers in the financial field ever since the original work by Fama (1970). The main factor behind the attention on the stock return volatility is that it informs on the stock price movement which in turn correlates to volatility in the entire stock market. This is further informed by the fact that a wellfunctioning stock market is vital for stability in the financial sector of any economy. A highly volatile stock return is unfavorable for the investors given the uncertainty in the market thus eroding their confidence in the same market.

Following the stock market crash in 1987, a lot of empirical analysis has been conducted in an attempt to model prediction of volatility in stock returns. As Schwert (1989) postulates, what cause volatility among stock returns still remains a puzzle. However, other empirical studies are precise on what causes volatility among stock returns and the relationship between stock prices and returns. Black and Scholes (1973), explicitly states that the stock prices are negatively related to stock returns and as a result of this, the investors will demand for high premiums to leverage on the volatility risk.

A review of the studies on the Nairobi Securities Exchange (NSE) reveals that there is limited research on the evidence on stock returns volatility. Using monthly data, Oluoch and Oyugi (2012) investigated the market risk (beta) using the Capital Market Pricing Model (CAPM) for different market segments at the NSE. They conclude that various equity investments segments of NSE exhibited unique factors that influenced segmental market risk. Returns for agricultural
segment were found to be the most volatile while financial and investment segment returns were the least risky for the period 2008-2011. The study is however mute on the nature of volatility for the different market segments; - Moreover, the period under review is biased given the post election violence of 2007/2008 and the global financial crisis that were likely to have exaggerated study findings. In addition the study utilized monthly data which is not suitable in analyzing market volatility.

This study therefore seeks to utilize the daily data in analyzing the volatility at the NSE by being capable of capturing volatility in the listed companies stocks as opposed to the earlier study that utilizes monthly data.

### 1.1.1 Stock Return

A return on stock is what an investor gains or losses on investing in a particular stock or portfolio. It is dependent on the inherent risk in the market that the stock is listed. The variations in the returns on investments are mostly dependent on the risk appetite of the investor; the more risk an investor is willing to take on, the more the returns to the said investor and vice versa. Sharpe (1964).

The most recognized model for calculating stock returns is the capital asset pricing model (CAPM) developed in the 1960s. Sharpe (1964), Lintner (1965) and Mossin (1966) separately developed the framework of the CAPM. They assumed on this model that capital markets are perfect and efficient and that there is free flow of information. Another assumption that they made was that there are no transactional costs, personal or corporate taxes. Investors were considered as risk averse single-period wealth maximizers and had similar security risk and return expectations. They also could borrow and lend at a constant risk free rate. Security
distributions were considered to be normal and that markets were diversified without unsystematic risk. Economies on the other hand were not affected by inflation.

### 1.1.2 Stock Returns Volatility

Volatility is a measure showing deviation or dispersions in returns in a particular stock return or the market portfolio as a whole. It is the characteristic risk associated with the particular stock and or market. In the efficient market theory, this inherent risk was assumed to be the systematic risk, (Fama, 1970), with the non-systematic risks expected to be fully diversified. Choi et. al, (2012) concluded that volatility exhibits three typical patterns in most financial time series, this characteristics are; clustering, asymmetry and persistence.

Many empirical studies have identified asymmetric volatility in stock price, where stock return volatility tends to go up more following a large fall in price rather than following a rise in price. However it has turned out to be difficult to see persistence in the stock prices in many empirical studies; difficult, if not impossible, to predict future asset returns from historical returns leading to conclusions in numerous studies that there is no predictability in the volatility of asset returns (Corsi, 2004). Volatility in the market will have an effect on how investors behave towards a market; higher returns encourage the investors to invest and increase their capital inflows, whereas in volatile environments the returns are unpredictable ultimately affecting investments.

Risk is the major factor that determines the returns with the higher risk the higher the return will be. Correctly modeling and forecasting volatility is important since volatility is a significant factor in many areas of finance, like in risk management, asset pricing and asset management (Fama, 1965). In the recent years, volatility has become a major aspect in the financial market that there are products introduced either to provide hedging or to be traded depending on the type
of investor in the market. It is because of these changes that researchers are interested in volatility forecasting.

### 1.1.3 Nairobi Securities Exchange

In 1954, the Nairobi Stock Exchange was constituted as a voluntary organization of stockbrokers registered under the Societies Act. In July 2011, the Nairobi Stock Exchange Limited changed its name to the Nairobi Securities Exchange (NSE) Limited reflecting its strategic plan to evolve into a full service securities exchange which supports trading, clearing and settlement of equities, debt, derivatives and other associated instruments (NSE, 2013). Demutualization process was initiated in 2006 by the formation of a demutualization committee and this process would improve management of the listed shares in the NSE; the process would see $51 \%$ of the NSE being publicly owned and therefore raising the browse to international standards by delinking ownership from management.

The same year, 2006, witnessed the establishment of the automated trading system (ATS) and an increased number of trading hours to 1500 hrs . There was cross listing of listed firms following the signing of the memorandum of understanding between NSE and the Ugandan Stock Exchange hence allowing dualism for companies listed in both exchanges (NSE, 2015). MSCI Barra classified Kenya as a frontier market (MSCI, 2013) in June 2013. As defined by the International Finance Corporation in 1992, frontier markets are markets that are investable but have lower market capitalization and liquidity. They are considered a subset of the emerging markets (EMs) (NSE, 2013). The frontier equity markets are typically pursued by investors seeking high, long term returns and low correlations with other markets. The implication of a country being labeled as frontier is that, over time, the market will become more liquid and
exhibit similar risk and return characteristics as the larger, more liquid developed emerging markets.

The NSE is one of the most vibrant financial securities markets in Africa after Johannesburg Stock Exchange and the Egyptian Stock Exchange. NSE is organized into eleven independent market sectors including: Agricultural, Commercial and Services, Telecommunication and Technology, Manufacturing and Allied, Banking, Automobiles and Accessories, Insurance, Energy and Petroleum, Construction and Allied Investment and Investment. In 2007, NSE reviewed the index and announced the companies that would constitute the NSE Share Index. In 2008, the NSE All Share Index, NASI, was constituted as an alternative index. Its measure is an overall indicator of the market performance. Focus was on the overall market capitalization rather than the price movements of selected counters (NSE, 2013).

In 2009, the automated trading in government securities marked a significant step in the efforts by the NSE and the CBK towards creation of a more liquid capital market; all government bonds were uploaded on the Automated Trading Systems (ATS). In January, 2013 the Growth Enterprise Market segment was launched with Home Afrika being the sole company registered under this segment. In 2014, the process of rolling out the Real Estate Investment Trust, REIT, begun to enable direct investments in the thriving real estate market through properties or mortgages. Exchange Traded funds and mutual funds are also marked for listing (NSE, 2015). The first inwards cross-listing occurred on December 14, 2012 with the entry of Umeme, the Uganda power distributor, onto the Main Investment Market Segment (MIMS) of the Exchange. The Exchange has entered into a partnership with Securities Trading Technology (STT) of South Africa to develop a local Derivatives Market, (NSE, 2015).

### 1.2 Problem Statement

From the existing financial literature, a well - functioning stock market is core for stability in the entire financial sector of the economy as well as promoting growth and investment by instilling investors with confidence; a highly volatile market shuns away investors due to reduced market confidence. In addition, high volatility in the market leads to the leverage effect where by the investor will demand for higher market premiums to compensate on any volatility risk. From the early works in the stock return volatility, a survey on the empirical evidence shows a positive relationship between stock return and its variance. To start with Black (1976), Christie (1982), Duffee (1995)) - report presence of leverage effect - negative relationship between stock returns and volatility in the market. Based on their works the relationship between stock returns and volatility has been the subject of a number of studies in finance literature. These studies report evidence of a negative and asymmetric relationship, that is, a negative stock return is generally associated with a large increase in volatility whereas the same magnitude of positive stock return is associated with a relatively small decrease in volatility.

On the other hand, Avramov Chordia, and Goyal (2006) claim that uninformed individual trading can generate an asymmetric and negative return - volatility relationship and that Hibbert,et al. (2008) suggest a positive association between asymmetric volatility and investors' behavioral biases. Similar results have been echoed by Chuang et al, (2011) who postulates that there exists a positive contemporaneous relation between trading volume and return volatility in Hong Kong, Korea, Singapore, China, Indonesia, and Thailand, but a negative one in Japan and Taiwan. It was found that a significant asymmetric effect on return and volume volatilities was in all sample countries and in Korea and Thailand, respectively.

This study will attempt to study:
i. Is there volatility clustering in the Nairobi Securities Exchange?
ii. Is there leverage effect among the stock returns for all listed companies at the Nairobi Securities Exchange?

### 1.3 Main Study Objective

The main objective of the study will be to investigate the dynamics of stock return volatility at the Nairobi Securities Exchange.

### 1.3.1 Specific Objectives

Specifically, the study seeks:

- To determine the effect volatility clustering has on stock returns at the NSE
- To determine the effect leverage effect has on stock returns at the NSE


### 1.4 Significance of the Study

This study makes three main contributions to the existing literature and policy. First, evidence on stock return volatility at the NSE in Kenya is scanty. Oluoch and Oyugi (2012) investigated the market risk (beta) using the Capital Market Pricing Model (CAPM) for different market segments at the NSE using monthly data. The study tries to bridge this gap using the high frequency daily data so as to properly capture even the short term developments in the market that may influence stock returns volatility. This will be of help to potential researchers in this field by providing background information as well as literature review.

On the policy front, understanding dynamics of stock return volatility in the banking sector at the Nairobi Securities Exchange will guide the regulator, Capital Market Authority, in developing measures that would dampen price volatility. Currently there has been debate on the introduction of financial derivatives, mainly futures, at the Nairobi Securities Exchange to leverage on market volatility (risks). Knowledge on dynamics of returns volatility will hasten this innovation as well as pricing of such financial products. In addition the currently listed companies often mirror the bigger picture on the volatility in the entire economy which will be of importance to CMA in formulating facilities geared towards lowering high volatility in the market.

Thirdly, to the investors, the understanding of stock market volatility is also important whether they are domestic and foreign investors. An investor will choose a portfolio mix that maximizes returns and minimizes risks. Theoretically, investor will choose portfolios along the efficient market frontier; portfolios that have assets with low risk and the same return or assets with high returns and low risk. Information on how frequent and persistent such volatility shocks are, will influence investors' portfolio choice as far as stocks for the listed copmanies at the Nairobi Securities Exchange is concerned.

## CHAPTER TWO

## LITERATURE REVIEW

### 2.1 Introduction

This chapter reviews the literature that is relevant to this area of study. The chapter starts by highlighting the main theoretical literature behind stock returns and stock returns volatility in the financial field. It then goes ahead to critically examine the empirical literature on the empirical studies carried out by different researchers in the field and lastly, the chapter gives a summary of the literature highlighting the existing gap that the study seeks to fill in.

### 2.2 Theoretical Literature Review

### 2.2.1 Capital asset pricing model

A review of financial literature in the asset pricing as far as the stock market is concerned, reveals that the capital asset pricing model (CAPM) is perhaps one of the oldest and well known theories in asset pricing. The theory is as a result of works advanced by Treynor (1961, 1962),[2] Sharpe (1964), Lintner (1965a,b) and Mossin (1966) independently, building on the earlier work of Markowitz on diversification and theory. It is applied in theoretically determining the appropriate required rate of return of an asset, if that asset is to be added to an already welldiversified portfolio, given that asset's non-diversifiable risk. The model of this theory mainly accounts for the asset's sensitivity to the systematic risk in the market mainly represented by a beta. In addition the model accounts for the expected return of the market and the expected return of a theoretical risk-free asset. In a nutshell, the CAPM suggests that an investor's cost of equity capital is determined by beta which is the measure of risk or the variance in the market returns. However, the model is criticized for a number of issues. First the measurement of the
market rate of return is unclear. Secondly, the model under this theory assumes a linear model, in that it assumes that the stock returns follow a linear model. This is not the case given that stock return derived from the stock prices is a high frequency data which follows a non - linear model. However, works by Keim and Stambaugy (1986), Fama and French (1988), Campbell and Shiller (1988), Ferson and Harvey (1991, 1993), Whitelaw (1994), Pesaran and Timmermann (1995), Pointiff and Schall (1998) Bossaerts and Hillion (1999) and Martijn Cremers (2002) postulate that the stock returns can be predictable by a linear model with some financial predictors such as earnings yield and some economic variables.

### 2.2.2 Autoregressive conditional heteroscedasticity model

Stock returns are highly volatile hence the need for a model that will appropriately capture volatility. In our case we assume that the conditional mean is constant while the conditional variance is not constant. Therefore, we use the Autoregressive Conditional Heteroscedasticity (ARCH) models introduced by Engle (1982) to model the conditional variance and asymmetry at the NSE. In these models, the volatility in stock returns at time $t$ is a function of exogenous, lagged endogenous variables and the past error term. Volatility cannot be observed hence must be estimated. Several models have been constructed to represent dynamics of stock return volatility in attempt to forecast it. One of the shortcomings of the ARCH model in the modelling and analysis of stock returns volatility is that it has only one memory period. Empirical evidence shows that high ARCH order has to be selected in order to catch the dynamic of the conditional variance. The high ARCH order implies that many parameters have to be estimated and the calculations get burdensome. The study will therefore be focused on the ARCH 1,1 model.

### 2.3 Determinants of stock returns.

From the reviewed literature, the main determinants of stock returns in the security markets can be broadly described in three major points:

Divided policy: Dividend policy is a major financing decision that involves payment to shareholders in return for their investments. It is important for investors because investors consider dividends not only the source of income but also a way to assess the firms, from investment points of view; It is the way of assessing whether the company could generate cash or not. Many investors like to watch the dividend yield, which is calculated as the annual dividend income per share divided by the current share price. Campbell and Shiller (1988) found a relationship between stock prices, earnings and expected dividends and he drives a conclusion that earnings and dividends are powerful in predicting stock returns over several years.

Risk: this refers to the uncertainty in what the investor expects from the market. It may range from the individual asset risk to the portfolio risk. From the financial literature there exists a negative relationship between the risk and the expected returns. High risks, scales down the returns from the asset through a reduction in the asset's price. However, there can exist a positive relationship between the risk and the returns from the asset in that due to higher risk, investors may demand for higher premium from the market. Therefore, market volatility being one of the risks will definitely affect the stock returns in the market.

Macroeconomic factors: macroeconomic variables especially the high frequency variables will tend to shock the stock market hence influencing the stock returns. Variables such as inflation,
interest rates and exchange rates all being high frequency data will have an impact on the stock returns.

### 2.4 Empirical Literature Review

A review of the empirical studies with regard to stock returns volatility posits that a number of works on this area has been undertaken with much being in the developed economies.

To start with, Poon \& S Taylor (1992) examined stock returns and volatility in U.K. context for the using daily, weekly, fortnightly and monthly returns on the Financial Times All Share Index from January 1965 to December 1989. The study obtained volatility estimates from monthly sample variances and ARCH models. The study found out that expected returns have a positive, though not statistically significant, relationship with expected volatility in returns. However, these findings are in complete contrast with the results of a latter study by Glosten, et al (1995) which resulted in a negative relation between conditional expected monthly return and conditional variance (monthly volatility in stock returns).

A large pool of empirical literature has been devoted to explaining this fact about the distribution of aggregate stock returns with pioneers of the work in this area being Fama, 1965, Black, 1976, Christie, 1982, Blanchard and Watson, 1982, Pindyck 1984, French et al., 1987, Hong and Stein, 2003 of late. A number of studies have focused on asymmetric volatility as an explanation for negative skewness in aggregate stock returns. Black (1976) and Christie (1982) develop the leverage effect where a low price leads to increased market leverage which in turn leads to high volatility (se ealso Veronesi, 1999). Pindyck (1984), French et al. (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), Wu (2001), and Veronesi (2004) develop the volatility feedback effect where high volatility is associated with a high risk premium and a low
price. Blanchard and Watson (1982) explain negative skewness as a result of the bursting of stock price bubbles.

While focusing on the stock returns volatility the question would be whether the stock returns of companies listed at the Nairobi bourse experiences volatility clustering. That is, are high returns followed by high returns and low returns followed by low returns?

Andersen et al, (2000) used direct model-free measures of daily equity return volatility and correlation obtained from high-frequency intraday transaction prices on individual stocks in the Dow Jones to test for the volatility clustering. Their study concludes presence of strong temporal dependence and appears to be well described by long-memory processes. Positive returns have less impact on future variances and correlations than negative returns of the same absolute magnitude, although the economic importance of this asymmetry is minor. Finally, there is strong evidence that equity volatilities and correlations move together, possibly reducing the benefits to portfolio diversification when the market is most volatile. Our findings are broadly consistent with a latent volatility factor structure, and they set the stage for improved highdimensional volatility modelling and out-of-sample forecasting, which in turn hold promise for the development of better decision making in practical situations of risk management, portfolio allocation, and asset pricing.

Lee et al, (2001) studied the features of stock returns and volatility in the Chinese stock market. From the study the variance ratio test rejects the hypothesis that stocks follow a random walk. Further, upon the application of the ARCH models, the study documents the evidence of long memory in Chinese stock returns. In addition the study confirms the presence of time varying volatility as well as predictability of stock volatility in stock returns. The findings totally
disagree with the results by Harvey (1995) which asserts that the emerging markets have high average stock returns, low volatility, low exposure to world risk factors and little integration. However, the findings that stocks do not follow a random walk are in tandem with the findings by Poterba and Summers (1988) who urged that stock returns do not follow a random walk but rather undergo mean reversion process. It's noteworthy that Lee et al, (2001) finding of presence of volatility clustering among the Chinese stocks is in consensus with the findings of the earlier studies by Baillie and DeGennaro (1990) on the dynamics of the expected stock returns and Volatility in the US stock market and Poon and Taylor (1992) study on the U.K market. Both the studies report the presence of volatility clustering, predictability and persistence of conditional volatility in both markets.

Al-Rjoub and Azzam (2012) studied financial crises, stock returns and volatility in Jordan's stock market by observing stock price behaviour during "crashes" and discovered that crises have a negative impact on stock returns and that the banking sector was most affected; There was evidence of high persistence in volatility and strong reverse relationship between stock return and its volatility before and after the crises. Wasim Ahmad (2015) investigated regime shifts and volatility in BRIICKS (Brazil, Russia, Indonesia, India, South Korea and South Africa countries) stock markets with a perspective on asset allocation and concluded that there was strong evidence of regime switching, between bearish and bullish, over the sample period and that the switching was associated with international and country-specific events that led to the fluctuations of those markets.

Elyesiani \& Mansur (1998) investigated Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate. The study employed the framework that discarded the restrictive assumptions of linearity, independence, and constant conditional
variance in modelling bank stock return thus allowing for shifts in the volatility equation in response to the changes in monetary policy regime in 1979 and 1982 to be estimated. ARCH, GARCH, and volatility feedback effects are found to be significant. Interest rate and interest rate volatility are found to directly impact the first and the second moments of the bank stock returns distribution, respectively. The latter also affects the risk premium indirectly. The degree of persistence in shocks is substantial for all the three bank portfolios and sensitive to the nature of the bank portfolio and the prevailing monetary policy regime.

For the French stock market we show that volatility is affected differently, depending on the recent past being characterized by returns all above or below a certain level. In the same way a longer term trend may also influence volatility. It is found that bad news is discounted very quickly in volatility, this effect being reinforced when it comes after a negative trend in the stock index. On the opposite, good news has a very small impact on volatility except when they are clustered over a few days, which in this case reduces volatility. Study by Asma and $\operatorname{Li}$ (2014) on regional volatility shows that stock return volatility is attributed to common rather than countryspecific factors. The study focused on 46 international markets in four regions: Asia, Europe, Latin America and Africa and common components were more stable in the European and Latin American countries than in the Asia-Pacific and African Countries.

Emenike (2010) modelled stock returns in Nigeria using the ARCH family models for January 1999 - December 2008 period using the monthly data. The study found revealed theta stock of the Nigerian bourse show volatility persistence and fat tailed distribution for the entire period analysed. Anchalia (2013) investigated the volatility in Asian stock markets considering four countries: India, China, Japan and Hong Kong and the global financial crisis and found out that
sub-prime crisis had a positive impact on the volatility of the returns of Japan, China and India while it had no impact on the volatility of returns of Hong Kong. The Eurozone debt Crisis had a negative impact on the volatility of the stock returns in India and China but not in Japan or Hong Kong. The author also noticed that volatility clustering, persistence, asymmetry and leverage effects' in stock returns series of Hong Kong, Japan, China and India.

Lanne (2002) concluded that stock returns are predictable by several strongly auto correlated forecasting variables, especially at longer horizons. It is suggested that this finding is spurious and follows from a neglected near unit root problem. However, the study finds no predictability for U.S. stock return data from the period 1928-1996. Adjasi (2009) studied macroeconomic uncertainty and conditional stock-price volatility in frontier markets concentrating in Ghana. Using macroeconomic variables such as inflation, exchange rate, interest rate, money supply, oil, gold and cocoa prices he found out that higher volatility prices in cocoa and interest rates increased stock price volatility while high volatility in gold and oil prices as well as money supply reduced volatility in stock prices. Yahchouchi (2014) in his study of whether return and volatility traverse the MENA-middle eastern and north Africa- stock markets borders found out that the markets are interconnected by their volatilities but not by their returns and that conditional volatilities exist across the markets, increasing during times of crisis and reducing to pre-crisis levels after. In his study it was also discovered with significant evidence that the conditional correlation was on a downward trajectory in some of the MENA stock markets and behaved differently.

Turning into leverage effect, we define is as the negative relationship between stock prices and volatility. Therefore under the leverage effect, stock prices and volatility are negatively related implying that the potential investors in the stocks will demand for a premium to hedge
themselves against any potential risks arising from the volatility in the market. Pyun et al (2000) in studying the Korean stock market found the presence of leverage effect implying that bad news have a greater impact on stock returns volatility than good news. The findings are consistent with the Goudazi and Ramamarayan (2011) who studied the effect of good and bad news on volatility in the Indian stock market using asymmetric ARCH model.

### 2.4 Chapter Summary

A keen survey of the empirical literature reviewed in this chapter reveals that analysis of developed stock markets dominates the studies with scanty research on emerging markets. It's also clear that the literature review in the preceding section reports mixed results, contradictory in some aw well as convergence in others

In a nutshell, from the reviewed empirical literature, there is likelihood that stock market volatility is largely determined by market's structure based on their setting - location, number of financial instruments traded, and changes in regulations over time among others. The disagreement among the empirical studies in literature makes it difficult to generalize volatility in stock markets either across different regions and time periods. There is therefore the need to study the market of our interest and where possible use a combination of econometric techniques for comparison purposes if we are to have clear insight on dynamics of stock returns in such markets. The study seeks to use daily stock data of all the listed firms in the NSE to test for stock return volatility.

## CHAPTER THREE

## RESEARCH METHODOLOGY

### 3.1 Introduction

This chapter focuses on the research methodology to be adopted in this study. It covers the study's research design and population to be studied, the empirical model to be estimated, data collection tools and analysis procedures.

### 3.2 Research Design

The study seeks to use an exploratory research design. In this case the study will try to give an in-depth insight into what is the nature of volatility of returns at the Nairobi Securities Exchange. By doing so, the study will seek to provide more detailed explanation on the volatility in the stock returns of all the listed companies at the NSE. The study will be a build up from the expected random walk hypothesis of the stock market to the hypothesis of volatility clustering and leverage effect in stock returns. By doing so, the study will lay out ground work on the future studies with regard to the stock returns for the banking segment at the NSE.

### 3.3 Population

The study aims at investigating the volatility in stock returns for all the sectors as represented in the Nairobi Securities Exchange. Therefore, the study analyzes the stock returns for all the listed companies at the Nairobi Securities Exchange. As a result the all the 64 listed companies will form the total study population. Since the study will focus on all the companies, therefore, there will be no sampling. The entire population will also be the entire sample for the study.

### 3.4 Data Collection

The study will utilize secondary data. The data will be obtained from the Nairobi Securities Exchange and will be composed of mainly the daily share prices for the all listed companies at the NSE from the period 2010-2013.

### 3.5 Data Analysis

In analyzing the volatility, high frequency data will be used as a result, the empirical model applied in the estimation of the data should be capable of capturing all the aspects of the high frequency data if credible and robust results are to be obtained. As a result, the study will employ the Autoregressive Conditional Heteroscedastic model (ARCH) pioneered by Engle (1988) in the estimation of the data. In this case $\operatorname{ARCH}(1,1)$ model will be used implying that we will have one Arch term and one period lag.

However, stock returns are assumed to follow a random walk process in an efficient stock market. Thus given this assumption, we define a simple random walk model as follows:
$\mathrm{R}_{\mathrm{t}}=\mu+\alpha_{1} \mathrm{R}_{\mathrm{t}-1}+\varepsilon_{\mathrm{t}}$.

Where $\mathrm{R}_{\mathrm{t}}$ is the daily the stock return at period $t$
$\mu$ - is the daily mean stock return
$\varepsilon_{\mathrm{t}}$ - is the error term at period $t$.

However, in reality stock market are inefficient and as such the random walk process hypothesis may fail in favor of the mean reversion process. Theoretically, the ARCH model is generally specified as follows:

$$
\begin{equation*}
y_{t}=y_{t-1}+\varepsilon_{t} \tag{2}
\end{equation*}
$$

$h_{t}=\sigma_{t}^{2}=\omega+\sum_{i=1}^{p} \alpha_{i} \varepsilon_{t-i}^{2}$.

Where:
$\sigma_{t}^{2} \quad-$ is the variance
$\omega, \alpha-$ are coefficients of the model, $\alpha$ is the arch term for the model
$\varepsilon_{t-1}^{2} \quad$ - Square of previous period's errors

Equation 2 is the mean equation while equation 3 is the variance equation. The variance equation uses the variance from the mean as the measure of volatility since variance measures the variation of the values of a variable from its mean value.
$h_{t}$ is the conditional variance of the daily stock returns signifying the conditional stock returns' volatility. In this case, the above ARCH model has q number of ARCH terms.

From the theoretical representation, we define our ARCH 1,1 model as follows
$R_{t}=R_{t-1}+\varepsilon_{t}$
$h_{t}=\sigma_{t}^{2}=\omega+\alpha_{1} \varepsilon_{t-1}^{2}$.

Where:

Rt - Is the daily the stock return at period t
$R_{t-1} \quad$ - Previous day daily returns
$\varepsilon_{t} \quad-$ Is the present period error term for the model.
$\sigma_{t}^{2} \quad$ - Variance of the model
$\alpha_{i} \quad$ - Arch term for the model
$\varepsilon-N\left(0, \sigma^{2}\right)$ implying that the error term is normally distributed with a mean of zero

The model ARCH model imposes restrictions; $\omega>0 \alpha \geq 0$ to ensure that conditional variance is non - negative. In addition, $\alpha+\omega$ measures the responsiveness of shocks to volatility over time. A sum greater that unity imply that shocks to stock returns are sustained over time while a sum less than unity imply that shocks decline over time. The $\alpha$ term is the ARCH term that measure then volatility clustering in returns. The closer the term is to unity implies substantial volatility clustering in the market implying that higher returns are followed by higher return while lower returns are followed by lower returns. On the other hand, the lower the value of the ARCH term, the lesser the volatility in the market ,implying that higher returns are not followed by higher returns and lower returns are not followed by lower returns.

Once the data on the share prices is obtained, stock returns will be generated using the formula $R_{t}=\left(P_{t}-P_{t-1} / P_{t-1}\right) \times 100$ Where $\mathrm{P}_{\mathrm{t}}$ is the current share prices, $\mathrm{P}_{\mathrm{t}-1}$ previous period share prices and $R_{t}$ is the stock returns. For the data analysis STATA will be used for regression and carrying out the diagnostic tests required to ensure robustness of the results obtained. Upon the generation of the stock returns, we will test for the stationarity of the returns to determine their order of integration. Upon testing for unit root, the ARCH model will be fitted to obtain the mean
equation coefficients and the variance equation coefficients. In addition to estimating the ARCH 1,1 model, the descriptive statistics for the stock returns will be will be computed to determine the distribution of the stock returns for the the listed companies at the NSE.

### 3.5.1 Volatility Clustering

The coefficients of the mean equation and the variance equation will be analyzed in order to achieve the objectives of the study. In order to determine the stock return volatility we refer to the coefficients of the empirical model to be estimated.

From the model the summation of $\alpha$ and $\omega ;-\left(\sum \alpha+\sum \omega\right)$ should total to unity. When $\left(\sum \alpha+\sum \omega\right)$ $=1$ implies that the shock to the present stock returns volatility is more likely to be persistent for a long time in the future. The implication here is that the current information still remains very important in predicting future stock prices and stock returns thus the market is a weak form efficient market. On the other hand, if $\sum \alpha+\sum \omega$ is very close to unity but not unity then there exists strong persistence of shock to stock returns and vice versa. The $\alpha$ term is the ARCH term that measure then volatility clustering in returns.

### 3.5.2 Leverage Effect

To achieve objective two on testing for the presence of the leverage effect, we estimate the Exponential Generalized ARCH model. The model is given as follows:
$R_{t}=R_{t-1}+\varepsilon_{t}$
$\operatorname{Ln}\left(\mathrm{h}_{\mathrm{t}}\right)=\operatorname{Ln} \sigma_{\mathrm{t}}^{2}=\omega+\beta_{j} \operatorname{Ln}\left(\sigma_{t-1}^{2}\right)+\alpha_{1}\left\{\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|-\sqrt{\frac{2}{\pi}}\right\}-\gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$.

Where:

| $\sigma_{t}^{2}$ | - Is the variance |
| :--- | :--- |
| $\varepsilon_{t-1}$ | - Is the previous period error term |
| $\sigma_{t-1}$ | - Is the previous period standard deviation |
| $\gamma$ | - Is the asymmetric coefficient |
| $\omega, \beta \& \alpha$ | -coefficients of the model. |

Equation 6 is the mean equation relating the current returns to the previous day returns. From equation 6 we obtain the standard errors which go into the estimation of conditional variance equation thus establishing the link between stock returns and volatility.

Equation 7 is the conditional variance equation. The coefficient $\gamma$ is known as the asymmetry or leverage term. The presence of leverage effects can be tested by the hypothesis that $\gamma<0$. The impact is symmetric if $\gamma \neq 0$ implying that there is not leverage effect in the market.

## CHAPTER FOUR

### 4.1 Introduction

The chapter covers data analysis and discussion of the results. It gives the descriptive statistics of the daily stock returns as well as the distribution of the daily returns. In addition the chapter covers the regression results for the Autoregressive Conditional Heteroscedastic (ARCH (1, 1) model and the Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH $(1,1)$ model results.

### 4.2 Empirical Results and Discussions

### 4.2.1 Restrictive statistics

Table 4.1 Descriptive statistics for daily stock returns

| Mean | 0.0425 |
| :--- | :---: |
| Median | 0.6741 |
| Minimum | -3.6910 |
| Maximum | 3.9926 |
| Std. Dev. | 0.6741 |
| Variance | 0.4544 |
| Skewness | 0.3597 |
| Kurtosis | 8.3786 |
| No. of observations | 1,002 |

From table 4.1 it's evident that there are 1,002 observations for the entire period under the study.
Looking at the mean values, we conclude that for the period under review, the daily mean of the stock returns is 0.0425 with a dispersion of 0.6741 from the mean as portrayed by the standard
deviation. The skewness value of 0.3597 suggests the daily stock returns for the January 2010 December 2013 are skewed to the right implying that the daily stock returns have been positive.

Turning to the kurtosis value, we find that the daily stock returns for the 2010-2013 are nonnormally distributed. This is because for the normally distribution the kurtosis value is equal to 3.0. This therefore implies that the daily stock returns for year 2010 - 2013 period are fat tailed hence portraying the characteristic of leptokurtosis.

Figure 1.1: Daily stock returns for January 2010 - December 2013 period


### 4.2.2 Unit Root tests

Prior to estimating the $\operatorname{ARCH}(1,1)$ and $\operatorname{EGARCH}(1,1)$ the unit root/ stationarity test was conducted. This was essential in order to determine the order of integration for the returns. From
the financial literature the stock returns are generally expected to be integrated of order zero. This is because, stock returns are basically derivatives of stock prices and since stock prices are integrated of order one, then, their derivatives (stock returns) must be integrated of order zero. For the unit root tests, both the Dickey Fuller tests and the Philip Peron (PPP) test were applied for robustness. This results for the test are presented in table 4.2.2.

Table: 4.2.2 Unit root tests results

|  | Dickey Fuller Test |  | Phillip Peron Test |  |
| :--- | :--- | :--- | :--- | :--- |
| ADF test <br> statistics | Calculated <br> Values | Critical Values | Calculated <br> Values | Critical Values |
| Returns | -20.53 | -3.430 (at 1\%) | -20.49 | -3.430 (at 1\%) |
|  |  | -2.860 (at 5\%) |  | -2.860 (at 5\%) |
|  |  | -2.570 (at 10\%) |  | -2.570 (at 10\%) |

From the unit root tests results, it's evident that the daily stock returns are stationary at level. This implies that they are integrated of order zero thus they conform to they generally laid down financial literature.

### 4.2.3 ARCH (1, 1) Results

Table :4.2.3 ARCH $(1,1)$ Results

|  | Coefficient | Std. Err. | Z statistics | $\mathrm{P}>\|\mathrm{z}\|$ | [95\% Conf | Interval] |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Mean Equation |  |  |  |  |  |  |
| Constant | 0.0220 | 0.0185 | 1.19 | 0.233 | -0.0141 | 0.0582 |
| Returns ( $\mathrm{R}_{\mathrm{t}-1}$ ) | 0.3642 | 0.0282 | 12.93 | 0.000 | 0.3090 | 0.4194 |
| Conditional Variance Equation |  |  |  |  |  |  |
| Constant ( $\alpha$ ) | 0.2579 | 0.0093 | 27.85 | 0.000 | 0.2397 | 0.2760 |
| Arch term ( $\omega$ ) | 0.3034 | 0.0394 | 7.70 | 0.000 | 0.2262 | 0.3806 |
| Number of obs $=1001$ |  |  |  |  |  |  |
| Wald chi2 $(1)=167.23$ |  |  |  |  |  |  |
| Prob $>$ chi $2=0.0000$ |  |  |  |  |  |  |

From the results, it's true that the previous day returns positively and significantly determines today's stock returns. This is evidenced by the positive coefficient of the previous day's return in the mean equation which is equal to 0.3642 and significant since its probability value is equal to 0.000 which is less than 5 percent. As a results, it's evident that one can predict today's stock returns from yesterday's stock returns meaning that the daily stock returns at the Nairobi Securities Exchange for 2010 - 2013 period do not follow a random walk process.

Turning to the conditional volatility equation, the ARCH effect is present and pronounced implying serial correlation in daily return. This is given by the coefficient of the Arch term which is equal to 0.3034 and highly significant with the $\mathrm{p}-$ value of 0.000 . This implies
significant volatility clustering at NSE for the period 2010 - 2013 meaning that low returns are followed by low returns while higher returns are followed by higher returns.

The sum $\alpha+\omega$ yields to $0.5603=(0.2579+0.3034)$ implying that he shocks to daily stock returns at the NSE for the period 2010-2013 are short lived and as such do not persist for a long period of time. This is because the sum is less than unity.

### 4.2.4 $\operatorname{EGARCH}(1,1)$ Results

Table 4.2.4 EGARCH $(1,1)$ Results

|  | Coefficient | Std. Err. | Z statistics | $\mathrm{P}>\|\mathrm{z}\|$ | [95\% Conf | nterval] |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Mean Equation |  |  |  |  |  |  |
| Constant | 0.0275 | 0.0189 | 1.46 | 0.144 | -0.0094 | 0.0644 |
| Returns ( $\mathrm{R}_{\mathrm{t}-1}$ ) | 0.3427 | 0.0253 | 13.56 | 0.000 | 0.2931 | 0.3921 |
| Conditional Variance Equation |  |  |  |  |  |  |
| Constant ( $\omega$ ) | 1.0159 | 0.0313 | -32.42 | 0.000 | 1.0773 | 0.9545 |
| Arch term ( $\beta$ ) | 0.0370 | 0.0370 | 1.89 | 0.059 | -. 00269 | 0.1425 |
| Asymmetry <br> ( $\gamma$ ) | 0.4828 | 0.0477 | 10.12 | 0.000 | 0.3892 | 0.5763 |
| Number of obs $=1001$ |  |  |  |  |  |  |
| Wald chi2 1 ) = 183.93 |  |  |  |  |  |  |
| Prob > chi2 $=0.0000$ |  |  |  |  |  |  |

To test for the leverage effect we ran the exponential $\operatorname{GARCH}(1,1)$ model. From the mean equation, it's true that the previous day returns positively and significantly determines today's stock returns. This is evidenced by the positive coefficient of the previous day's return in the
mean equation which is equal to 0.3642 and significant since its probability value is equal to 0.000 which is less than 5 percent. This confirms the results of the ARCH $(1,1)$ model estimated previously.

From the variance equation model, the $\operatorname{Arch}(1)$ term $(\alpha)$ is positive and significant throughout the models signalling the presence of volatility clustering hence positive daily returns are followed by positive daily returns and negative daily returns are followed by negative daily returns at the NSE. The Garch term ( $\beta$ ) measures the persistence of the volatility shocks in the market.

On asymmetry, $\gamma=0.4828$ revealing significance presence of asymmetry at thus, bad and good news drive the daily stock returns outcomes at NSE. This implies that the asymmetric response of conditional variance enters the evolution of stock returns at the Nairobi Securities Exchange with a further implication of presence of idiosyncratic shock. As results, there was significant leverage effect at NSE during 2010-2013 period implying that a rise in the stock prices is negatively related to the stock returns.

### 4.2.5 Summary and interpretation of findings

From the data analysis we can deduce the following findings of the study:

The daily stock returns at the NSE do not follow a random walk model. This implies that the present day stock returns cannot be predicted from the previous day returns thus rejecting the existence of random walk hypothesis for the period under review. Secondly, high returns are followed by high return and low returns are followed by low returns implying presence of volatility clustering in the market. However we note that this clustering only exists for a short
period of time and therefore fades out in the long run. Thirdly we conclude that leverage effect is present inn NSE though not very persistent. This implies an element of information asymmetry in the market.

From the above summary and interpretation of the findings, relating these findings to the finding of the previous studies reviewed under empirical literature review yields the following comparison results. With regard to leverage effect, the findings of the study are in tandem with Glosten, et al (1995) who reports negative relationship between stock returns and stock volatility. Similar conclusions are arrive at by (Veronesi, 1999), Pindyck (1984), French et al. (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), Wu (2001), and Veronesi (2004) who develop the volatility feedback effect where high volatility is associated with a high risk premium and a low price implying a negative relationship between stock returns and stock volatility. Similar results are alluded to by Al-Rjoub and Azzam (2012). This agrees with Pyun et al (2000) and Goudazi and Ramamarayan (2011) who reports presence of leverage the Korean and Indian stock market stock respectively.

Turning to random walk hypothesis testing, we find that daily stock returns at the NSE do not follow a random walk model. This finding concurs with the findings by Lee et al, (2001) who rejects the random walk hypothesis in the Chinese stock market. The findings are further in agreement with Poterba and Summers (1988) who urged that stock returns do not follow a random walk but rather undergo mean reversion process.

## CHAPTER FIVE

## SUMMARY, CONCLUSION AND RECOMMENDATIONS

### 5.1 Introduction

This study analyzed the volatility in conditional stock returns at Nairobi Securities Exchange for the period $2^{\text {nd }}$ January 2010 to $31^{\text {st }}$ December 2013. The study used the ARCH - family econometric models to test for both the stock returns volatility at the NSE. More specifically, the study focused on the following objectives: Determine the effect of volatility clustering on the stock returns at the NSE and to determine the effect of leverage effect on the stock returns at the NSE

To achieve objective one, $\operatorname{ARCH}(1,1)$ was estimated. The arch term was analysed to deduce as to whether volatility clustering exist at NSE and how it affects the daily stock returns in the market. To investigate the persistence of these volatility, the sum $(\alpha+\omega)$ was obtained where the sum of close to unity implied long term persistence in volatility clustering while a sum of close to zero implied the volatility clustering are short lived.

To achieve objective two on testing for the presence of the leverage effect, we estimate the Exponential Generalized ARCH model. The mean equation for Exponential Generalized ARCH was used to relate the current returns to the previous day returns whereas the conditional variance equation for Exponential Generalized ARCH was used to establish the link between stock returns and stock returns volatility. The presence of leverage effects on stock returns was tested was concluded to be present if the asymmetric coefficient of the model $(\gamma)$ is less than zero while the impact is symmetric if $\gamma \neq 0$ implying that there is no leverage effect in the market. The
study found no presence of random walk in daily stock returns. I addition, volatility clustering and leverage effect were both found to be present though not persistent.

### 5.2 Conclusion

From the data analysis the following conclusions were4 arrived at. First, Nairobi Securities Exchange is not a weak - form efficient market as evidenced by the significant coefficients of the previous day's returns in determining the present day's returns. Since the one day lag returns significantly influence the current day's returns, then the stock returns for the period under review do not follow a random walk hypothesis. The finding is in tandem with This finding concurs with the findings by Lee et al, (2001) and Poterba and Summers (1988) who urged that stock returns do not follow a random walk. We can therefore conclude from the finding that daily stock returns at NSE undergo mean reversion process implying that despite how high or how low the stock returns are at a given moment in time, they tend to revert back to their mean values with time.

Secondly, on volatility clustering is evident at the NSE as portrayed by the significance of the coefficients of the ARCH (1) terms implying that high returns are followed by high return and low returns are followed by low returns. However, the shocks to the daily stock returns are shorty lived and decay at a short interval. This is because, the sum $\omega+\beta<1$ and not close to unity at all. We therefore conclude that the upswings and downswings evidenced at NSE have short live span and therefore the risk averse investors in the market are short investment horizons.

Thirdly, the leverage effect is confirmed at the NSE for the period under review. This implies the existence of information asymmetry in the market. Therefore, the stock returns and the market volatility are negatively related meaning that in the time of high market volatility, the bearish
behaviour rules the market while in the time of low volatility bullish behaviour takes an upper hand in the market.

### 5.3 Recommendations to Policy and Practice

From the study findings, a number of policy implications can be deduced. First the evidence of volatility clustering imply that high returns are followed by high return and low returns are followed by low returns. This informs decision making during the bullish or bearish behaviour in buying or selling of stocks. When high returns are followed by high return the market tends to be bullish meaning that investors can sell their stock for a higher return. As such during this time majority of the investors especially the risk averse ones and up being net sellers rather than net buyers. On contrary, when low returns are followed by low return the investors tend to be net buyers rather than sellers since stock prices are on their lowest.

In addition, the presence of volatility clustering effect indicates the volatility in daily stock returns is time varying. In other words, portfolio managers and equity investors should adjust their portfolio management practice in response to the traditional risk measure of unconditional variance in order to minimise the risk that comes as a result of serial correlation in stock returns over time. The short live nature of volatility clustering on stock returns imply that the investors at the NSE have short term investment horizon who are mainly keen in either reaping the capital gains or the dividend earnings within the shortest time possible.

The negative relationship between the stock returns and market volatility is in tandem with the financial theory. Thus in order to make the market efficient, dissemination of information to shareholder and investors at large would help in reducing information asymmetry and thereby enhancing better performance for the listed firms by enhancing transparency and reducing the
information costs which is in itself a cause of market inefficiency. Enhancing transparency thus reducing asymmetry will also be crucial in reducing the leptokurtosis in stock returns thus reducing abnormal gains that would cause market turbulence that arises from high market volatility.

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## APPENDICES

## Unit Root test

```
dickey-Fuller test for unit root
```

Number of obs =
778

|  | Test | 1\% Critical | 5\% Critical | 10\% Critical |
| :---: | :---: | :---: | :---: | :---: |
|  | Statistic | Value | Value | Value |
| Z ( t ) | -20.532 | -3.430 | -2.860 | -2.570 |

MacKinnon approximate $p$-value for $Z(t)=0.0000$

## pperron Returns

```
Phillips-Perron test for unit root
```

Number of obs =

|  | Test | 1\% Critical | 5\% Critical | 10\% Critical |
| :---: | :---: | :---: | :---: | :---: |
|  | Statistic | Value | Value | Value |
| Z (rho) | -562.132 | -20.700 | -14.100 | -11.300 |
| Z (t) | -20.493 | -3.430 | -2.860 | -2.570 |

[^0]
## ARCH (1, 1) Results

ARCH family regression

| Sample: 07jan 2010-31dec2013, | Number of obs $=$ | 1001 |
| :--- | :--- | :--- |
| Distribution: Gaussian | Wald chi2(1) | $=$ |
| Log likelihood $=-888.7036$ | Prob $>$ chi2 | $=167.23$ |


| Returns | Coef. | OPG |  | $\mathrm{P}>\|\mathrm{z}\|$ | [95\% Conf | Interval] |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Std. Err. | z |  |  |  |
| Returns |  |  |  |  |  |  |
| RT | . 3641634 | . 0281606 | 12.93 | 0.000 | . 3089697 | . 4193571 |
| _cons | . 0220474 | . 0184872 | 1.19 | 0.233 | -. 0141867 | . 0582816 |
| ARCH |  |  |  |  |  |  |
| L1. | . 3034486 | . 0393915 | 7.70 | 0.000 | . 2262427 | . 3806544 |
| _cons | . 2578775 | . 0092582 | 27.85 | 0.000 | . 2397318 | . 2760233 |

## Exponential Garch Results (EGARCH)

## ARCH family regression

| Sample: 07 jan2010 - 31dec2013, but with gaps | Number of obs | $=1001$ |
| :--- | :--- | :--- |
| Distribution: Gaussian | Wald chi2(1) | $=183.93$ |
| Log likelihood $=-898.7067$ | Prob $>$ chi2 | $=0.0000$ |



| L1. | .4827727 | .0477194 | 10.12 | 0.000 | .3892443 | .5763011 |  |
| ---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  |  |  |  |  |  |  |  |
| _cons $\mid$ | 1.015882 | .0313343 | -32.42 | 0.000 | 1.077297 | .9544683 |  |


[^0]:    MacKinnon approximate $p$-value for $Z(t)=0.0000$

