LAGGED DISTURBANCES AND VOLATILITY OF SECTORAL RETURNS IN THE NAIROBI SECURITIES EXCHANGE, KENYA

BY

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This thesis is my original work and has not been presented for a degree in any other University

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To Jacob M’Mukuchia and Elijah M’Kararu

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OPERATIONAL DEFINITION OF TERMS

ARCH Effects ARCH effects is a statistical property that is deemed present in a time series variable if the squared residuals of fitting an autoregressive model to this variable are autocorrelated.

Asymmetric Response to Shocks This is the tendency of negative shocks to cause higher levels of volatility in security returns than positive shocks of the same magnitude.

Bear Run This is a period of time during which security prices in an entire financial market go down in a systematic manner.

Blue Chip Sectors A blue-chip sector is a market sector that mostly comprises highly capitalized and well established firms that have been operational for a relatively long period and have attained respectable market leadership.

Bull Run This is a period of time during which securities that are traded in an entire financial market are systematically appreciating in value.

Cross Past Shocks These are shocks to a market sector from a given previous period that gets transmitted to other interrelated sectors thereby elevating their volatility in a designated present period.

Cross Past Volatility This is volatility of a market sector in any given past period that spills over to other interrelated sectors, ostensibly via the contagion effect, thereby elevating the volatility of these sectors in the designated present period.

Drift The drift of a time series process is a constant term by which the observed value of the process at any given time must be adjusted with when estimating the next period's observation.

Exogenous Variables These are variables in a causal system whose value is either partially or wholly independent from other variables in the system. The value of exogenous variables is determined outside the causal system.

Financial Contagion Financial contagion is the spread of market disturbances in one market sector to other sectors. This phenomenon is primarily evident in sectors that have a high level of interdependence, since it's mainly propagated via financial and economic links.

Idiosyncratic Volatility Idiosyncratic (or unsystematic) volatility is a type of volatility that is not manifested systematically in all sectors of a market, but it has a propensity to only one market sector.

Lagged Disturbances This is the totality of past influences (own & cross past shocks and own & cross past volatilities) that have implications on the level of volatility in a given market sector as at a specified time.

Large Capitalization Stocks These are stocks that have a large market value. Usually, large capitalization stocks are defined as stocks with a market capitalization that is above the median market capitalization of all stocks that are listed in an exchange.

Latent Variable Latent variables are variables that cannot be directly observed and hence their values must be inferred from the values of other observable variables.

Liquidity In the context of a securities market sector, liquidity is defined as the ease with which stocks of the pertinent sector can be sold or bought without necessitating a drastic change in their prices.

Mean Equation This is an autoregressive model for estimating the returns of a security at a given period as a function of the previous period's returns. Mean equations tend to have heteroscedastic residuals; and the time-varying variance of these residuals is the most common measure of volatility in econometrics.

Mean Reversion Mean reversion is the tendency of financial time series to revert to their long-run mean regardless of the degree of short term deviations.

Order of Integration In time series analysis, the order of integration refers to the number of times that a non stationary time series variable must be differenced in order to make it stationary.

Own Past Shocks These are shocks to a market sector from a given previous period that influence its level of volatility in the period which has been designated as the present.

Own Past Volatility This is volatility of a market sector from a specified past period that is persistent such that it influences the levels of volatility of this sector in a specified present period.

Shock For any given time, the differential between the actual returns of a sector and its expected returns is referred to as a shock. Shocks are caused by the arrival of new information in the market about a sector. Good news cause a positive shock (realization of returns that are higher than expected) while bad news cause a negative shock (realization of returns that are lower than expected).

Small Capitalization Sectors	These are stocks that have a small market value. Usually, small capitalization stocks are defined as stocks whose market capitalization is below the median market capitalization of all stocks that are listed in an exchange.
Stationary at Levels	A time series variable is deemed to be stationary at levels if its level (first instance) observations do not have a unit root and it therefore needs no transformation at all to attain stationarity.
Temporal Dependence	This is an attribute that is deemed to exist in a variable whose value at any given time is dependent on its own observations or observations of other variables from a previous time.
Volatility	The level of turbulence of a market sector's returns. Sectoral volatility for any given period is modelled as a function of shocks that impacted this market sector and other interrelated market sectors in the previous period and the level of volatility in the respective sector and other sectors that are interlinked with it in the previous period.
Volatility Clustering	Volatility clustering is a characteristic of financial securities which holds that large changes (of either sign) in security value tend to follow large changes and small changes (of either sign) tend to follow small changes.

Volatility Persistence Volatility persistence is tendency of a sector's volatility at any given period to have sustained impact on its levels of volatility for future periods

ABBREVIATION AND ACRONYMS

ADCC	Asymmetric Dynamic Conditional Correlation
AR(1)	Autoregressive Model of Order one
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
BEKK	Baba - Engle - Kraft - Kroner
BRICS	Brazil, Russia, India, China and South Africa
CAC Index	*Cotation Assistée en Continu* Index
CEA	Chinese Economic Area
DCC	Dynamic Conditional Correlation
DSE	Dar Es Salaam Stock Exchange
EGARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
FIEGARCH	Fractionally Integrated Exponential GARCH
FMCG	Fast Moving Consumer Goods
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFEVD	Generalized Forecast Error Variance Decomposition
IRF	Impulse Response Function
JSE	Johannesburg Stock Exchange
KES	Kenya Shilling
LSE	London Stock Exchange
LM	Lagrange Multiplier

MA	Moving Average
MGARCH	Multivariate GARCH
MPT	Modern Portfolio Theory
NASDAQ	National Association of Securities Dealers Automated Quotations
NSE	Nairobi Securities Exchange
NYSE	New York Stock Exchange
PLC	Public Limited Company
S&P	Standard & Poor
TGARCH	Threshold GARCH
UAE	United Arab Emirates
USD	United States Dollar
USE	Uganda Stock Exchange
VAR	Vector Auto regression
VARMA	Vector Autoregressive Moving Average
VECM	Vector Error Correction Model

ABSTRACT

The securities market plays an integral role in any well functioning economy. In particular, it helps in raising of equity capital, provision of investment opportunities, and transfer of funds from surplus agents to deficit agents. In order to attain Vision 2030, the Nairobi Securities Exchange (NSE) is expected to play a key role in the economic pillar of this blueprint by perpetuating the mobilization of resources for implementation of envisaged flagship programs and projects. However, despite the key importance of the NSE in the local and regional economy, this market has exhibited high levels of volatility of returns. This is inferred by the huge responses to sectoral and systematic shocks that have been observed in the NSE, as well as extant empirical evidence of high levels of volatility persistence in its sectors. Therefore, it is vital to understand the NSE sectors' shock and volatility transmission linkages since this can enhance portfolio selection processes, help in forecasting of future sectoral volatility, and guide market regulators in mitigating the adverse effects of shock and volatility transmission. The main objective of this study was to establish the extent to which volatility of sectoral returns in the NSE, as at any specified time period, is influenced by lagged disturbances. In particular, the study investigated the influence of own past shocks; cross past shocks; own past volatility; and cross past volatilities on the volatility of each NSE sector. Further, the study also investigated the moderating effect of liquidity on the relationship between own past volatility & shocks and volatility of each NSE market sector. Weekly secondary time series data for the 6th June 2008 to 8th February 2019 period was used for all analysis processes. The study utilized a VAR(1)BEKK MGARCH(1,1) model to investigate the influence of lagged disturbances on sectoral volatility in the NSE. The moderating effect of liquidity on own shock and volatility transmission effects was appraised using the Irwin and McClelland (2001) two step process and estimation of GARCH(1,1) models as well as GARCH(1,1) models with exogenous variance regressors. All empirical analysis was undertaken using the *WinRATS* Version 10 software package. Results indicated that own past shocks influence volatility of all NSE sectors. In addition, volatility of each sector of the NSE in any given week was found to be responsive to cross shocks from the previous week, although the prevalence of these effects wasn't uniform across all sectors. Moreover, the study found evidence of significant own volatility transmission effects in six NSE sectors. Further, there was evidence of cross volatility transmission linkages in all sectors, though these linkages were more prevalent in some sectors than others. The study also found out that liquidity moderates own shock and volatility transmission effects in the Agricultural, Automobiles & Accessories, Commercial & Services, and Energy & Petroleum sectors only. On the basis of these results, several policy implications of the study are outlined: When sectoral shocks are detected, investors and portfolio managers should prepare for an elevation of idiosyncratic volatility in the near future and undertake mitigation measures in advance, depending on the shock transmission linkages of the affected sector(s). Regulatory authorities should also monitor markets proactively and be ready to enforce administrative measures to prevent speculative gains and dramatic losses that can lead to a spike in volatility immediately after a major sectoral shock. Moreover, portfolio managers and investors should use the unveiled shock transmission patterns in tandem with their respective portfolio allocation strategies when choosing the sectors to invest in. Additionally, investors should avoid forming portfolios with stocks of sectors that are linked by shock and volatility transmission linkages. Finally, since the study found out that liquidity moderates the transmission of own shocks and own volatility in four NSE sectors, it is suggested that volatility management measures for portfolios that include stocks from these four sectors should be robust enough to take into account the extant moderating effect on liquidity.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The securities market plays an absolutely essential role in any well functioning economy. The main functions of a securities market is to facilitate efficient raising of capital (Levine, 1991), mobilizing and channeling of capital from entities with excess liquidity to those with deficient liquidity (Kalu, 2014), and providing an avenue for portfolio diversification (Mishra, Swain, and Malhotra, 2007; Jebran and Iqbal, 2016). In the Kenyan context, the Nairobi Securities Exchange (NSE) is expected to play a key role in the economic pillar of Vision 2030 by perpetuating the mobilization of resources for implementation of flagship programs and projects. The ultimate aim of these efforts is attain increased and sustainable economic growth that will anchor the socio-economic well being of Kenyans (Kilonzo, 2012).

Despite the apparent importance of securities markets, several challenges that have major implications on their efficiency do exist. According to Katzke (2013) uncertainty about the prospects of market players tops the list of impediments to market efficiency. Podmajerska (2016) concurs and notes that the global financial crisis of 2007-08 is an excellent illustration of the damage that market uncertainty can cause. In that crisis, market downturns that began in the NYSE soon led to carnage in LSE, NASDAQ and other major markets of the world. Therefore, it is extremely important for investors and other market players to have a solid understanding of the issue of market volatility, its determinants, and transmission patterns within and between financial markets. Occurrence of extreme volatility in a market induces investor aversion (Ibbotson, 2011). In such cases, market participants may be unable to distinguish between high risk securities and less riskier ones. Such inability to distinguish

between securities on the basis of their risk is called adverse selection, and it can make the players to shun all market securities thereby leading to total market collapse. This underscores the kind of danger that volatility portends for securities markets. Caporale, Hunter & Ali (2014) note that excessive volatility is an unattractive feature of contemporary securities markets in that it magnifies uncertainty about securities' future prospects thereby impeding asset allocation decisions of market participants. Additionally, it can lead to a situation where investors demand a risk premium for each security that is commensurate with its risk profile and its transmission linkages for shocks and conditional volatility. Therefore, it is crucial to investigate the subject matter of volatility in security markets with a view of getting a better understanding of its propagating mechanisms. This can inform market participants' decisions thus mitigating the adverse effects of volatility.

Engle (1982) is the bedrock on which modern understanding of volatility and its influencing factors is built. This study observed that volatility in a market is driven by the tendency of the actual market returns in any given period to differ from those that were previously anticipated. Edwards (1998) refers to the differential between actualized and expected returns as a 'shock' and notes that arrival of new information in the market is what causes shocks. Good news cause positive shocks (realization of returns that are higher than expected) while bad news cause negative shocks (realization of returns that are less than expected). Engle and Ng (1993) describe the level of volatility in a market at any time period to be conditional, in that it depends on the magnitude of shocks from prior periods. The implication is that the more actual returns for past periods differed from the returns that were expected for these periods, the higher the level of prevailing uncertainty in the market. Ng (1993) further posits that the influence of past shocks on volatility tends to decrease with passage of time and at

any given time; the most recent shocks have the highest influence on the level of volatility while shocks that occurred many periods ago have a lesser influence.

Bollerslev (1986) discovered that in financial markets, there is a significant degree of autocorrelation between the levels of volatility that are observed in successive periods. Bollerslev, Engle and Wooldridge (1988) denoted this attribute as 'persistence' of volatility and attributed it to the fact that adjustment to new information in markets isn't usually instantaneous. Instead, it takes a number of time periods for the effect of shocks to be reflected significantly in the level of volatility. Therefore, volatility in one period feeds onto the volatility of the next period: the level of volatility in any given period is largely attributed to the level of volatility in the previous period, which in return is also informed by the level of volatility of its preceding period. Building on precedence from the literature, the present study therefore hypothesized that in addition to past shocks; past sectoral volatility is also an important determinant of the level of sectoral volatility at any given time.

Engle and Kroner (1995) note that there is a tendency of past shocks and past volatility of a market sector to be transmitted to other sectors, thereby affecting the volatility of returns in these sectors too; in addition to that of their sector of origin. This phenomenon is known as "cross spillover" of shocks and volatility effects (Ebrahim, 2000). It has been proven empirically that taking into account a definite lag between returns series; interrelated sectors tend to have a high level of comovement of returns, especially during times of financial crises (Engle and Sheppard, 2001). This effect, by extension, means that shocks and volatility in one sector have an influence on the future volatility of other related sector(s).

According to Johansson (2010), there has been a surge in the level of integration within various sectors of economies around the world in the recent past. Mohammadi and Tan (2015) opine that with increased interdependence and integration of economies' sectors, transmission of shocks and volatility across listed securities has posed a major challenge to investors' volatility management measures. Due to interlinkages of market sectors, it has become essential for market stakeholders to know how shocks and volatility are transmitted over time across different sectors of the same market and across sectors of different security markets. Hurditt (2015) concurs and notes that awareness of shock and volatility transmission patterns that are extant in markets could help investors and policy makers to take interventionist actions on time thereby mitigating the adverse effects of this transmission.

The discovery of cross spillover effects fundamentally changed the theory of volatility. Consequently, contemporary researchers on market volatility tend to investigate the volatility of a market sector as a function of the pertinent sector's own past shocks & volatility and cross past shocks & volatilities from other sectors. Therefore, the present study opined that it is essential to understand how past own and cross shocks and past persistent own and cross volatilities affects the level of volatility in the Nairobi Securities Exchange, current as at any specified time.

1.1.1 Past Shocks

The arrival of new information in the market about a particular sector influences investor actions with respect to the pertinent sector. For instance, good news about a sector will stimulate demand of its securities and consequently, its market value will rise above the level that it would have been at in the absence of this information. Conversely, investor disinterest will ensue if bad news on a sector arrives in the market. Due to the decline in market demand,

the market value of this sector will fall below the level that it would have assumed if the adverse news were not disseminated (Bollerslev, 1986). This implies that good news will lead to an actualized return that is higher than the previously expected return. Likewise, bad news will result in actualization of a return which is lower than the previously expected return. In the econometrics literature, the differential between the actual return and the expected return in every period, occasioned by the arrival of news, is referred to as a shock (Engle, 1982; Engle, Ito and Lin, 1990). A large shock implies that the news is "significant" or "big" in the sense that it produces a large unexpected change in market value. A common finding is that prevalence of shocks to a market sector's returns tends to heighten the level of uncertainty in this sector. Additionally, the surge of volatility that is induced by shocks sometimes tends to be persistent, thus influencing subsequent levels of volatility in the pertinent sector asymptotically into the future.

In any market sector, more recent news have a higher explanatory power for the level of prevailing volatility, at any given time, as compared to old news. Essentially; the older the news, the less effect it has on volatility (Engle and Ng, 1993). Chua, Goh and Zhang (2010) add that shocks can be thought of as the unexpected returns of a market sector for any trading period. Further, they posit that unexpected returns are the most important driver of idiosyncratic risk in market sectors. Therefore, sectors that have high fluctuations in unexpected returns have a higher level of unsystematic risk as compared to sectors whose unexpected returns do not experience extreme fluctuations. Engle and Kroner (1995) note that shocks occurring in any given period have a direct impact on volatility only in the succeeding period. For all subsequent future periods, the effect of shocks is not manifested directly in the present volatility but indirectly through the persistence of the volatility that was brought about by these shocks.

According to Engle and Patton (2001), a single realization of a sectoral shock can be defined as the extent to which the actual return of a sector for a given time period differs from the expected return for that sector due to the influence of a definite exogenous factor that impacted the sector in the specified period. Clements and Todorova (2014) further note that the level of volatility in a market gets adjusted by the shocks that arrive in the market in every single trading period. This implies that huge shocks to a given sector will increase the level of this sector's volatility in the succeeding period while tiny shocks will barely have any impact on the level of volatility. Past shocks fall into two broad categories: own past shocks and cross past shocks.

1.1.1.1 Own Past Shocks

Own past shocks of a sector are all shocks that impacted this sector's returns for past periods, upto a specified number of lags, prior to a specified point time (Bollerslev, 1986). The study sought to understand how volatility in each of the sectors of the Nairobi Securities Exchange in any given week is affected by these sectors' own shocks from the previous week.

In line with the econometrics literature, own lagged shocks of any given market sector, *i* were measured using the first lag of the square of the residuals of this sector's returns. The residuals were squared to preclude the possibility of the own past shocks variable collapsing to zero. If this variable is taken at levels, collapsing will be the inevitable consequence since residuals follow a mean reverting white noise process with a mean of zero and finite variance (Brooks, 2008; Engle and Patton, 2001). After fitting the empirical model, a relatively big and statistically significant coefficient for the own past shocks variable (relative to the size of other sectors' coefficients) of a given sector indicates a sizeable response this sector's volatility to its own past shocks. This is an undesirable feature since it indicates a low level of

robustness in the concerned sector as far as the tendency of withstanding shocks is concerned (Ho and Tsui, 2004).

1.1.1.2 Cross Past Shocks

Although the volatility in a market sector is largely influenced by its own past shocks, there is evidence in the literature that it can also be affected by past shocks of other securities (Apte, 2001). This phenomenon, referred to as cross spillover of shocks, is prevalent in markets where the level of sectoral interrelatedness is significant. A sector's cross past shocks are all shocks that impacted the returns of other sectors (which are somewhat interrelated with the sector of reference) for periods prior to the current time (upto a specified lag length) and have an effect on this sector's volatility (Engle and Kroner, 1995).

Jati and Premaratne (2017) add that a significant influence of one sector (such as agriculture sector)'s cross lagged shocks on another related sector (such as food processing sector)'s volatility is an indication of the presence of shock transmission effects from the agriculture sector to the food processing sector. This essentially implies that these sectors are linked by a shock transmission mechanism. Consequently, a shock to the agriculture sector (such as an abrupt introduction of a punitive tax on fertilizer) will be manifested in the volatility of returns of the food processing sector shortly thereafter. Therefore, the stocks that are listed under these two sectors can't jointly form a well diversified portfolio due to the cause and effect linkage that exists between their shocks and volatility respectively. The present study investigated how volatility of each NSE sector, in any given week, is influenced by cross shocks from the previous week.

As per the literature, cross past shocks to one NSE sector (for instance sector *i*) from other NSE sectors (for instance sectors *j*) were measured using the first lag of the squares of residuals of sectors *j*'s returns (Engle and Kroner, 1995; Bauwens *et al*, 2006).

1.1.2 Past Volatility

Volatility in the market does not adjust instantaneously to changes in its driving forces. Instead, it takes time to die off; with the rate of decay being different for the various sectors. This attribute is known as volatility persistence and it implies that lagged volatility, when used as an explanatory variable in an autoregressive specification, can be useful in estimating current volatility (Engle and Patton, 2001). Fryzlewicz (2007) concurs by adding that at any given point in time, the level of volatility in any market sector is autoregressive since it depends, to some extent, on its own levels from previous periods. Past volatility can be categorized into two broad types: own past volatility and cross past volatility.

1.1.2.1 Own Past Volatility

According to Engle (2001), the best predictor of volatility for a market sector in a particular period is its long run average past volatility. Bollerslev (1986) concurs by adding that volatility is autoregressive and hence the volatility of financial time series processes tends to exhibit high levels of autocorrelation between successive observations. If a sector has a relatively big coefficient for own past volatility, this means that volatility in this sector is highly persistent. The implication is that the pertinent sector's volatility for any given period largely depends on its volatility in the previous period, which by extension, depends on the levels of own volatility observed in periods prior to the previous period. The study evaluated the extent to which the level of volatility in the NSE sectors in any given week *t* are influenced by its respective level in the preceding week. In line with the literature (Engle,

1982; Brooks, 2008), own volatility of any given market sector, *i* was measured using a single lag of the conditional variance of the residuals of this sector's returns.

1.1.2.2 Cross Past Volatility

At times, volatility in one sector of the market tends to spread out such that it influences the volatility of other sectors in subsequent periods. This phenomenon is known as cross volatility spillover or financial contagion, and it mostly results from interdependence among market sectors (Badrinath and Apte, 2013). Ceballos, Hernandez, Minot and Robles (2016) illustrate the cross spillover of volatility effect using data of agricultural prices. They find out that when there are huge shocks to corn prices (such as drought in corn growing regions or imposition of huge tariffs on corn exports), these shock inevitably increases the volatility of corn prices in the succeeding periods. Since wheat is a substitute product for corn, increase in corn prices will lead to an approximately equivalent increase in wheat prices. As such, the increment in volatility of corn prices will definitely translate to a higher volatility of wheat prices.

Hosny (2013) adds that transmission of disturbances across sectors mostly takes place because of their financial linkages. This situation arises when volatility in an asset leads to future volatility in a related asset due to adverse selection and resultant aversion of investors towards the affected sector and all sectors that are somewhat related to it. The study was keen on evaluating how the volatility of each sector of the NSE in any given week is affected by the volatility of its other sectors in the previous week. In line with the literature, cross past volatility from NSE sectors (for instance sectors *j*) to another sector (for instance sector *i*) was measured using the first lag of conditional variance of the residuals of sectors *j*'s returns (Engle and Kroner, 1995; Bauwens *et al*., 2006).

1.1.3 Liquidity

Liquidity is defined as the degree to which stocks of a particular sector can be quickly sold or bought without necessitating a drastic change in their prices (Elliot, 2015). The level of liquidity in a market sector tends to play an integral role in the magnitude of the effect of lagged shocks and lagged volatility on volatility in this sector. If liquidity is high, the implication is that the proportion of listed shares that exchange hands in the pertinent sector in any given period is also high (Baumöhl, Kočenda, Lyócsa and Výrost, 2018). Therefore, shocks and volatility of such sectors at any given week have a higher probability of influencing their volatility in the following week, due to the existence of a robust mechanism to perpetuate these effects - a high level of investor participation and stock turnover.

On the other hand, shocks and volatility of less liquid sectors in any given week have a suppressed transmission mechanism, and their ability to influence the level of volatility in the following week is curtailed. This is due to the relatively low turnover and dimmed investor interest that is endemic in such sectors (Gaudesaboos, 2014). It is apparent therefore that the level of liquidity in any given market sector has the ability of determining the strength of the relationship between the independent variables (own past shocks & own past volatility) and the dependent variable (volatility). Consequently, the study tested, on a sector-by-sector basis, the moderating effect of liquidity of the momentum of transmission of own shocks and volatility.

In the study, liquidity was measured using a single lag of the aggregate weekly share turnover ratio. For each sector, this measure was computed by dividing the number of constituent firms' shares that were traded in each week with the total number of tradable shares (issued by its constituent firms) as at the end of each week (Goyenko, Holden and Trzcinka, 2009).

When testing for moderation effects, the moderator was multiplied by independent variables to create interaction terms. The moderator and the first lag of these interaction terms were then included as exogenous variables of the interaction models.

1.1.4 Volatility of Returns

Volatility of returns refers to the level of market turbulence in a particular market sector as at the time of reference, usually designated as time *t*, conditioned on all past information prior to this time (Bollerslev, 1986). The volatility of any market sector is denoted as conditional due to the fact that it incorporates all available past information with respect to the past shocks of this sector and of other related sectors and past conditional variances of this sector and of other related sectors (Engle, 1982; Bollerslev, 1986; King and Wadhwani, 1990; Engle and Kroner, 1995). Engle and Kroner (1995) state that volatility is an autoregressive moving average (ARMA) process of second order moments. This implies that the level of volatility in a market sector at any point in time can be explained by past values of itself and by past shocks or 'news' that affected the sector's returns prior to the time of reference.

Engle (2001) adds that with respect to a given point in time, the best predictor of a market sector's volatility in the next period is a weighted average of this sector's long run past volatility upto the current time; and new information, evidenced by its shocks/unexpected returns for the present period. Therefore, the current period's unexpected returns can be thought of as a Bayesian updating mechanism for the next period's volatility. Engle (2001) is corroborated further by Johnston and Scott (2000) who note that the level of volatility in any market sector can be explained largely by the tendency of volatility in this sector to be persistent and the ability of the arrival of new information to affect the level of turbulence in the sector (Bauwens *et al*, 2006). As in the literature (Engle, 1982; Bollerslev, 1986),

volatility of any given market sector *i* was measured in the present study using the conditional variance of the residuals of the pertinent sector's returns as at any given time, *t*.

The present study focused on investigating how volatility in the sectors of the Nairobi Securities Exchange is impacted by own and cross lagged volatility and shocks; and how liquidity moderates the relationship between own past shocks & own past volatility and current volatility. Modeling volatility dynamics is crucial for market players since it helps analysts to set volatility expectations for their various positions in the market. This offers them reasonable guidance for making asset allocation, advisory, and portfolio management decisions *a priori.* Furthermore, using current data on the predictors of future volatility, i.e. current volatility and current shocks, it is possible to forecast future volatility for the next period, or even several future periods, when a sufficient number of lags has been incorporated in a fitted model. This ability to forecast volatility is essential in that it can help investors and other market participants to estimate the future levels of volatility that they should anticipate for the various market sectors, thereby enabling them to undertake mitigation measures on time. Such measures can include selling securities whose sectors have extremely high levels of forecast volatility.

1.1.5 The Nairobi Securities Exchange

This study was based on the Nairobi Securities Exchange (NSE). Located in Nairobi, Kenya, the NSE dates back to 1954 when it was registered as a stockbroker's professional services firm. Over the years, the market has grown tremendously and is currently the largest securities market in East and Central Africa. Presently, the NSE has 64 listed equities that are categorized under 13 sectors (Nairobi Securities Exchange, 2019). There has been evidence of time varying volatility in the NSE in the past. This is clearly outlined in Figure 1.1 which

shows the time plot of weekly closing values of the NSE 20 share index from 1st November 2004 to 31st May 2008 - a time frame that wasn't part of this study's data collection period.

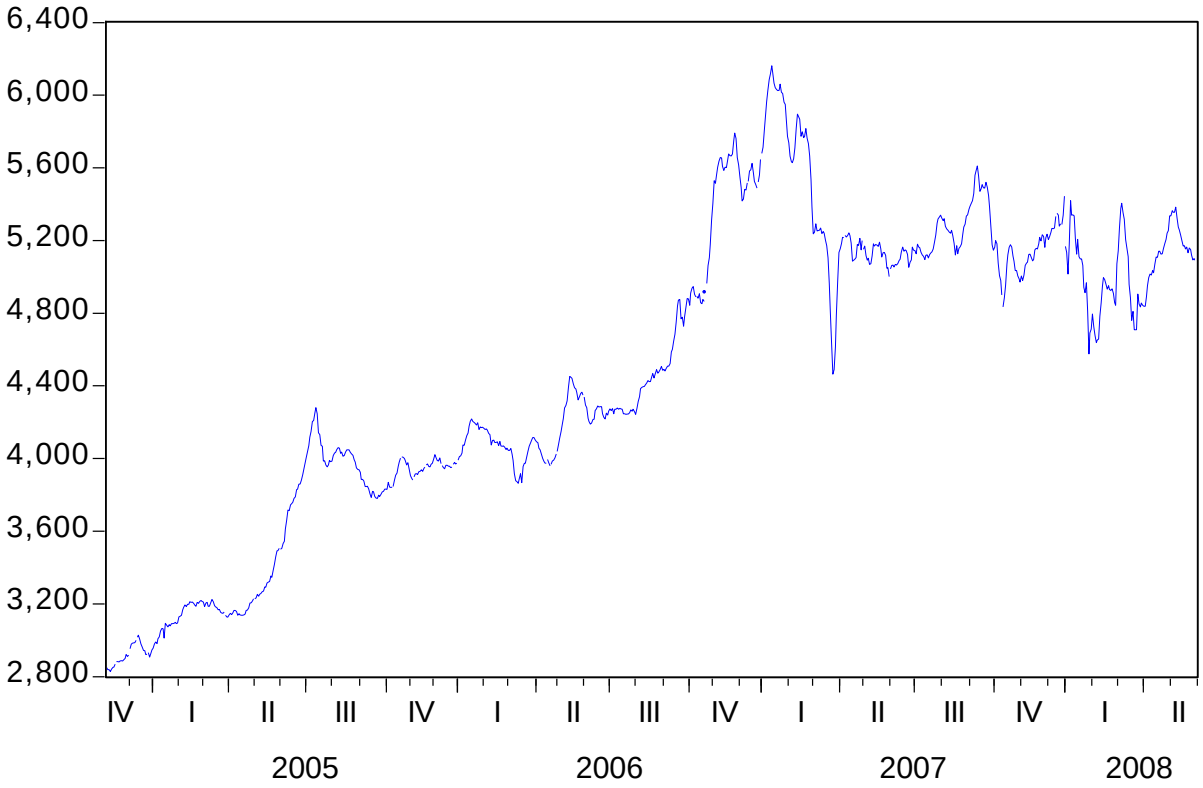

Figure 1.1: Weekly Closing Values of the NSE 20 Share Index

Source: Researcher's Computation (2016)

It can be noticed that the NSE 20 share index had an overall upward trend from November 2004, albeit with sporadic declines. This appreciation peaked in the fourth quarter of 2006, after which the index went into an extreme decline in the first quarter of 2007. For the better part of 2007 and 2008, the index was characterized by extreme volatility. There were many cycles of decline and recovery. The trend shows a particularly intense period of turbulence in the last quarter of 2007 and first quarter of 2008, a phenomenon that can ostensibly be attributed to the effects of the global financial crisis and the Kenyan post election violence.

Despite the fact that this illustration shows that there is prevalence of volatility in the NSE, there is a deficiency of empirical research pertaining the dynamics of volatility in this market, more so at the sectoral level. The current study therefore sought to plug this gap.

1.2 Statement of the Problem

The existence of intra-market volatility linkages in security markets is a well proven fact (King and Wadhwani, 1990). The Nairobi Securities Exchange has been no exception to the time varying levels of turbulence that arise as a result of exogenous shocks and persistence of volatility. For instance, Nairobi Securities Exchange (2016) warns that the 2016 introduction of interest rate caps on banking stocks is a shock that would cause high levels of volatility in the returns of banking stocks. This is a crucial issue since these stocks account for over a third of the NSE's total capitalization. Further, this report continues, the wave of volatility which was generated by this shock in the banking sector could get transmitted via a knock-on effect to affect the volatility of returns of pension funds, investment funds, and portfolios of other private and institutional players who invest in the banking stocks.

Guguyu (2017) notes that the unexpected nullification - a major shock - of the Kenya presidential election on 30th September 2017 caused NSE listed stocks to post a cumulative loss of Kshs 50 billion in only 10 minutes and trading had to be suspended momentarily to avert further losses. The report further adds that the period between the nullification and repeat of the poll was marred with wild fluctuations of asset values due to persistence of the high level of volatility that was brought about by the shock of results nullification.

Otiato (2018) observes that failure by parliament to repeal interest rate cap regulations was a negative shock which affected the returns of banking stocks adversely. In particular, Kenya

Commercial Bank lost 2.2% of its market value while Equity Bank lost 1.1% of its value after the window for repeal of the law elapsed in September 2018 without any legislative action from the National Assembly. Ogum, Beer and Nouyrigat (2015) posit that large shocks to crucial sectors (such as the Energy & Petroleum and Banking sectors) of the NSE can disrupt their returns as well as the returns of other sectors of this market thereby elevating the level of systemic volatility in the whole market. Moreover, volatility that is induced by large shocks to the fundamental sectors can persistently influence the volatility of the entire market for many periods into the future through the contagion effect.

Nevertheless, the Nairobi Securities Exchange is earmarked as a key entity of the economic pillar within the Vision 2030 context. In this blueprint, the NSE is expected to be instrumental in long run mobilization of resources that are required to fund other envisaged programs and projects which are aimed at enhancing socio economic welfare in Kenya (Kilonzo, 2012). Therefore, awareness of shock and volatility transmission patterns in the NSE is absolutely important.

Contemporary research has shown sectoral volatility in securities markets to be largely driven by its own momentum and momentums of related sectors' volatilities. Moreover, there is evidence that the level of sectoral volatility gets adjusted by shocks of the pertinent sector and those of related sectors via a shock spillover mechanism (Khan, 2013; Engle, Ito and Lin, 1990; Fleming Kirby and Ostdiek, 1998).

Before undertaking any portfolio selection processes, a key priority of the sophisticated investor therefore is to investigate how past shocks and past volatilities impact volatility within and between sectors of security markets. In particular, investors should use portfolio

selection criteria that take into account the possibility of cross transmission of lagged shocks and volatility in addition to traditional methodologies - such as Markowitz diversification. In other words, the significance and direction of volatility and shock transmission patterns between sectors is now a crucial factor of consideration in contemporary portfolio selection (Li and Yip, 2014). Therefore, this study deemed it necessary to undertake an investigation into the effect of lagged shocks and volatilities on sectoral volatility in the Nairobi Securities Exchange. Besides, past studies in the local scenario are not conclusive in that they don't consider all market sectors but focus only on own volatility transmission effects in a few NSE sectors while ignoring cross spillover effects of volatility and both own & cross spillover effects of shocks (Chuchu and Olukuru, 2015; Owidi and Waweru, 2016). Moreover, other local studies (Kirui, Wawire and Onono, 2014) only focus on how systemic volatility in the NSE 20 share index's returns is influenced by past cross shocks of macroeconomic variables, but do not delve into intra-market volatility dynamics within the sectors of the NSE.

As evident above, there was an essence on conducting a comprehensive research on transmission of sector-level shocks and volatilities in the NSE. Moreover, there was a need of investigating the moderating effects of liquidity on transmission of own shocks and volatility in sectors of the Nairobi Securities Exchange. This was due to the fact that there is evidence in the literature that the level of liquidity in a sector influences the speed of transmission of its own shocks and volatility, i.e. the time lapse before the effects of past own shocks and past own volatility are reflected in conditional volatility (Baumöhl, Kočenda, Lyócsa and Výrost, 2018). It is against this background that the study sought to plug in the gaps by exploring the dynamics of shock and volatility transmission in the sectors of the Nairobi Securities Exchange, thereby providing evidence on how sectoral volatility in the NSE reacts to past

shocks and persistence of lagged volatility; and how sectoral market liquidity moderates the influence of own past shocks and own past volatility on current sectoral volatility.

1.3 Research Objectives

The study was guided by the following objectives:

1.3.1 General Objective

The general objective of this study was to investigate the influence of lagged disturbances on volatility of sectoral returns in the Nairobi Securities Exchange, Kenya

1.3.2 Specific Objectives

The study was guided by the following specific objectives:

1. To investigate the effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.
2. To evaluate the effect of cross past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.
3. To examine the effect of own past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.
4. To establish the effect of cross past volatilities on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.
5. To appraise the moderating effect of liquidity on the relationship between own past shocks and own past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

1.4 Research Hypotheses

In order to achieve the objectives of this study, the null hypotheses below were tested:

H_{01}: There is no effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{02}: There is no effect of cross past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{03}: There is no effect of own past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{04}: There is no effect of cross past volatilities on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{05}: There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

It is noteworthy that the hypotheses posited above were tested on a sector by sector basis. Based on the results of data analysis, the study would reject a certain hypothesis for one sector but fail to reject the same hypothesis for some of the other sectors.

1.5 Significance of the study

This study is beneficial to diverse entities. In particular, it has five major contributions as discussed below:

The first major ramification of this study is that it provided empirical evidence on own and cross transmission effects of shocks and volatilities in the NSE's sectors; in terms of its presence, significance and properties. Additionally, it investigated how liquidity moderates the propagation rate of own shock and volatility transmission effects in the various sectors of

the NSE. Since there is a shortage of literature on the subject matter in the East African region, this study is of importance to researchers in this subject.

Second, the results of this study are expected to enhance the advancement of existing theories on shock and volatility transmission effects. Theories that were developed from empirical data of developed nations such as the modern portfolio theory, efficient market hypothesis theory, financial integration theory, and contagion theory stand to get validation based on the results of this study. This can help the knowledge community to affirm the applicability of these theoretical frameworks to developing economies or propose revisions to ensure their compatibility with the scenario in developing countries.

Third, the study is of essence to market players, such as investors and portfolio managers, since it can enhance their ability to make rational portfolio selection decisions. Furthermore, market players can be able to structure more robust portfolios than they otherwise would do without the results of this study. Moreover, the results of model fitting are also helpful in that they can help in forecasting of sectoral volatility, thus enabling market participants to calibrate their volatility management strategies with high precision.

Fourth, regulatory authorities of financial markets will be able to use the results of this study as a basis for action in response to the effects of shock and volatility transmission thereby enhancing confidence in securities markets. Additionally, the ability to forecast future levels of sectoral volatility will help them in undertaking mitigation strategies in good time.

Finally, securities markets' executives will find this study useful in understanding the internal dynamics of their markets that had been, hitherto the study, hidden in raw data. This will help them to institute the necessary management actions to mitigate the adverse effects of shock and volatility transmission, thereby enhancing the market participation experience for all market players.

1.6 Scope of the Study

This study was conducted using secondary time series market data from the NSE. Its geographical scope was the confines of the republic of Kenya in which all the firms that were listed on the NSE during the data collection period are domiciled. The data collection period was 6th June 2008 to 8th February 2019 - a total of 555 weekly observations for each sectoral index. The data collection period was set to start on 6th June 2008 due to two main considerations: Firstly, this date ensured that period of the global financial crisis of 2007/2008 was largely excluded, thereby minimizing the prospective confounding effect of this event on the study. Secondly, this is the date on which the shares of NSE's most dominant stock - Safaricom PLC - commenced trading. An earlier start date for data collection would have caused the data for Safaricom PLC to be excluded from the study and this could have distorted the face validity of the study. The study sought to ensure the inclusion of this stock due to its sheer importance. The market value of Safaricom PLC accounts for a very high proportion of the total market value of the NSE. For instance, as at 18th December 2018, the total market capitalization of the Nairobi Securities exchange was 2.413 trillion Kenya Shillings. 44% of this amount (1.062 trillion Kenya Shillings) was attributed to the market capitalization of Safaricom PLC (Cytonn Investments Management Plc, 2018).

1.7 Organization of the study

This part outlines the structure of the five chapters that constitute this thesis. Chapter one starts with an articulation of the background of the study, outlining of the study variables and a write-up on the Nairobi Securities Exchange. Next, the statement of the problem is discussed followed by an elucidation of the research objectives and the hypotheses of the study. Finally, the significance, scope, and organization of the study are articulated. Chapter

two commences with a brief introduction followed by a comprehensive review of theoretical and empirical literature. The chapter then culminates with a presentation of the study's conceptual framework. Chapter three is concerned with the research methodology of the study. It starts with a discussion of the research philosophy and research design. The empirical model for data analysis is articulated next. Next, the operationalization and measurement of variables, target population, study sample and sampling design are outlined. This is followed by a discussion of the study's data collection process and the methods for data analysis. Chapter four illustrates the data analysis procedures that were undertaken to yield the results of this work. It also outlines the main inferences of testing the study's five hypotheses. Chapter five contains a summary of the study's findings, conclusions, contribution to knowledge, policy implications, limitations, and suggestions for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, existing literature on the subject matter of the study was reviewed. The opening section of the chapter is a theoretical review of literature. Existing theories by previous authors to explain various aspects of the study were articulated in this section. Next, empirical literature on the relationship between the independent variables and the dependent variable was reviewed. After this, a summary of the reviewed empirical literature was outlined and the research gaps that this study sought to fill were also delineated. Finally, the conceptual framework was outlined and elucidated.

2.2 Theoretical Review

The theoretical review section outlines theories that are relevant to the subject matter of the research, and which resonate with broader aspects of the areas of knowledge under consideration (Abend, 2008). In this study, the theoretical review was triangulated in that there is not a single underpinning theory. Instead, it was jointly underpinned by the following theories: Efficient Market Hypothesis, Contagion Theory, Modern Portfolio Theory, and Financial Integration Theory.

2.2.1 Efficient Market Hypothesis

The efficient market hypothesis was proposed by Eugene Fama in 1970. This theory holds that in an efficient market, security prices at a particular point in time reflect all information that arrived in the market prior to the point of reference. The implication is that security prices are unpredictable on the basis of historical data, and investors have no opportunity to

earn an abnormal profit. Therefore, it's only the arrival of new information in the market - which happens in a random fashion - that can cause a change in security prices (Fama, 1970).

Fama (1970) posited that market efficiency falls in three categories: weak form, semi strong form and strong form. The weak form of the EMH holds that historical prices of securities are already reflected in their current prices, and therefore seeking to make any trading gains on the basis of historical price information is in vain. This implies that technical analysis cannot be used to predict future stock prices since the public has access to all past data on stock prices at zero cost. The semi strong form of the EMH holds that all publicly available information, including historical price data, is reflected in the current security prices, and therefore, superior returns cannot be achieved through the utilization of either the fundamental analysis approach or the technical analysis approach. Finally, the strong form of the EMH asserts that all available information (including insider information) is reflected in the stock prices, and no group of investors at all should be able to consistently derive abnormal profits. However, this form of EMH is rather untenable since insiders usually tend to have access to privileged information way before it reaches the public domain. The point is that insiders cannot benefit unduly from trading on the basis of insider information because should they try to do so, asset prices will simply shift to a new equilibrium level thereby eliminating opportunities for abnormal profits.

Since the EMH theory holds that only the arrival on new information can lead to a change in asset prices, it is consistent with this study as it holds that shocks (unexpected returns) are the only mechanism of introducing fresh adjustments to the level of sectoral volatility. In the absence of the influence of new shocks, volatility will decrease and decay progressively, depending on its level of persistence in the pertinent sector. Further, the study analogously

proved that the weak form of efficiency does not exist in the sectors of the NSE, since price movements were found to be predictable on the basis of their past observations and past shocks in all NSE sectors. The implication of this outcome is that investors in the NSE can predict sectoral volatility on the basis of past shocks and volatility (Khan, 2013).

2.2.2 Contagion Theory

Conceptualized by Bon (1885), the contagion theory seeks to explain individuals' actions in response to other individuals' moves. Blumer (1969) used this theory to explain that humans have a socio-psychological tendency to replicate the actions of other people even when they do not have a clear justification of doing so. In the financial markets sense, contagion refers to the tendency of volatility in one market sector to spillover such that it elevates the volatilities of other sectors. Financial contagion has been the main culprit in perpetuating major episodes of financial crisis and cross spillover of shocks and volatility since the late 1980s. In particular, the theory was found relevant in studies on the black Monday incident in the NYSE in 1987, the 1994 Mexican peso crisis, the Asian financial crisis of 1997 and the Russian rubble crash of 1998 (Baur, 2006).

In order for a disturbance to a market sector to be deemed as a contagion flow, it must be of a sufficient magnitude to elevate subsequent volatility even in sectors that are totally unrelated to the impacted sector. Contagion can therefore be seen as an excessive spillover of volatility from a sector in crisis to other sectors beyond any idiosyncratic links and fundamental linkages that may exist between them (Baur, 2006; Cheung, 2009; Sakthivel *et al*., 2012). Contagion can be measured by comparing the covariance between the returns of two sectors in times of relative stability and in times of crisis (such as after the impact of a major shock).

Consequently, contagion is deemed present if there is a statistically significant rise in sectoral covariance during times of turmoil (Forbes and Rigobon, 2002).

Following this approach, it can be hypothesized that if the returns of any two sectors of the NSE have weak to moderate correlation during periods of stability (such as the Manufacturing & Allied and Investment Services sectors) and then a shock to one sector creates ripple effects that lead to a significant increase in co-movement of returns with the other sector, this would constitute contagion. On the other hand, presence of contagion would not be necessarily inferred if two sectors that have a traditionally high correlation of returns (such as the Manufacturing & Allied and Energy & Petroleum sectors) continue to be highly correlated after a shock to one sector births new volatility which then spills over to the other sector. Contagion therefore is deemed present only if cross-sector transmission of volatility increases significantly after the impact of a cross shock. If volatility in a market sector does not increase significantly due to a cross-shock from another sector, any continued high level of sectoral co-movement suggests strong actual linkages between the two sectors - a phenomenon referred to as interdependence (Favero and Giavazzi, 2002).

The contagion theory is linked with the study in that it can be used to explain volatility transmission linkages between different sectors of the market. Unearthing the existence and nature of these linkages in the NSE was part of the mandate of this study. In mapping the sectors of the NSE that are susceptible to occurrence of contagion flows, the study enriched the portfolio selection processes of NSE market players. Best practices (Hammoudeh, 2014) suggest that investors should avoid including securities from sectors that have volatility transmission linkages in the same portfolio.

2.2.3 Modern Portfolio Theory

The modern portfolio theory (MPT), proposed by Markowitz (1952), holds that investors should construct a portfolio that is efficient in that it contains only securities with the highest returns for any given level of risk. Additionally, in order to reduce portfolio risk, the returns of securities in a portfolio should not have high levels of covariance. Therefore, a well diversified portfolio should contain securities that are drawn from different industries. The quality of diversification would be even higher if such industries do not share economic characteristics (Worthington and Higgs, 2004). Fleming, Kirby and Ostdiek (1998) improved the MPT theory by using mean-variance portfolio optimization to define the relationship between volatility of market returns and demand for financial securities. In particular, they posit that the volatility of a security's returns has an inverse causal link with the market demand for this security. The study further explains that transmission of own volatility would arise from persistence of volatility from the initial incidence of a shock while cross sector transmission of volatility might be attributed to portfolio managers' tendency to take hedging positions in different sector. Additionally, cross sector transmission of volatility might occur in instances where an information event, that alters demand and supply expectations of securities in one sector, results in implications on securities' demand and supply in other sectors.

This study is linked to the modern portfolio theory in that its findings could be utilized to enhance the efficiency of the MPT. Inasmuch as investors could diversify the securities in their portfolios in the best way possible, shock and volatility transmission reverses the beneficial effect of diversification because if these securities are linked by a shock and volatility spillover mechanism, the current shocks and volatility in one of these securities will

inevitably be reflected in the volatility of the other security at some future date, and this will amplify the level of overall portfolio volatility (Rejeb and Boughrara, 2015).

In addition to constructing their portfolios with assets that have a negative correlation of returns - as per the Markowitz diversification strategy - investors should further ensure that securities which are included in their portfolios are not linked by shock and volatility transmission mechanisms. The study augments the Modern Portfolio theory by outlining the sectors of the NSE that are linked by shock and volatility transmission mechanisms, thereby providing a basis for enhancing the portfolio processes of NSE market players.

2.2.4 Financial Integration Theory

The financial integration theory was proposed by Stockman (1988) who defined financial integration of capital markets as the process through which the returns of market sectors follow similar patterns over a long period of time. Since the global financial crisis, stock markets have witnessed considerable gradual movement of capital from the traditionally heavily traded blue chip sectors to small capitalization sectors and new sectors such as those containing emergent technologies stocks. This is because these stocks have good prospects due to fact that they are largely anchored in growth industries. Therefore, they have a potential for higher earnings and superior diversification opportunities (Johansson, 2014). This equalization of the sectors' relative importance has led to cointegration of price movements even in sectors where such movements were previously countercyclical to each other. Lucey and Kearney (2004) note that these developments have accelerated the level of integration between market sectors, and this has caused an even higher level of comovement of sectoral returns and volatility. These trends, they note, can result in higher systemic risk and amplification of future instances of contagion. Sectors of financial markets have also

become increasingly integrated due to a rapid increase in the level of input-output relations between the products and services that are traded under the various sectors (Sakthivel, 2010; Lucey and Kearney, 2004). In such circumstances, shocks to one sector or group of sectors can easily reverberate across the entire financial system and volatility in a particular sector tends to persist in this sector and in other sectors equally due to trade and financial linkages (Chuang *et al*, 2007).

According to Badrinath and Apte (2002), the tendency of traditional investors to seek diversification opportunities in thinly traded sectors can have ramifications on the abilities of firms listed in these sectors to pursue independent growth and business development objectives. These investors can impact directly on the strategic decisions of the thinly traded firms if their acquire stakes that give them major voting power. In particular, they might want to augment the operations and strategic direction of these firms and force them to implement policies that are consistent with those of the large stocks that ostensibly attribute for a major proportion of their portfolios; thereby advancing the agenda of integration even further (Nnachi, 2013; Chuang *et al*, 2007; Sakthivel *et al*, 2012).

The study is linked with the financial integration theory in that it provides evidence on the effects of financial integration. Although integration makes markets to be seamlessly connected, excessive levels of integration also reduce the quality of diversification opportunities in the market. This study obtained evidence on the prevalence of cross spillover patterns of shocks and volatility in the NSE, apparently in sectors that are extensively integrated. In doing so, it provided empirical proof which can guide policy on mitigation steps that can be undertaken to maintain an optimum level of market integration.

2.3 Empirical Review

This section presents a review of empirical studies that have been hitherto conducted by previous authors, in line with the study objectives. Essentially, it outlines what previous authors found out on the subject matter of this study.

2.3.1 Own Past Shocks and Volatility of Returns

Baumöhl and Liócsa (2014) investigated the effect of past shocks on volatility in eight emerging European markets: the Czech Republic, Hungary, Poland, Croatia, Estonia, Latvia, Lithuania, and Romania. The study applied the asymmetric dynamic conditional correlation (ADCC) model and found out that in emerging European markets, the asymmetric response to shocks effect is not quite pronounced. The paper found positive own past shocks to have as much effect on volatility as negative own past shocks. It also found a positive relationship between correlations of the returns and volatility. This led to the conclusion that diversification effects diminish during times of crisis, due to the increment in volatility which occurs in such times.

Choo, Loo, and Ling (2011) investigated shock transmission patterns between large capitalization stocks and small capitalization stocks in the Malaysian Securities Exchange. The study used time series data on sectoral indexes for these two categorizations. The main finding was that own lagged shocks have a large impact on volatility in large capitalization stocks as compared to small capitalization stocks. In other words, own shock transmission effects were found to be more prevalent in large capitalization stocks *vis a vis* small capitalization stocks. Moreover, this study found evidence that there was a surge in own shock transmission effects in both small and large capitalization stocks during and after the Asian financial crisis.

Using the BEKK (Baba - Engle - Kraft - Kroner) Multivariate GARCH (MGARCH) model, Antonakakis (2008) examined shock and volatility spillovers of four major currencies - the Euro, the British Pound, the Japanese Yen and the Swiss Franc - before and after the introduction of Euro. For both periods, the study found significant persistence of volatility arising from past own shocks to these four markets. The Yen had the highest level of such effects followed by the Euro, the Swiss Franc, and the British Pound respectively. This implies that past shocks to the Yen were most influential on its volatility, while shocks to the Pound were weakest in terms of their ability to influence the future volatility of this currency. However, the tendency of past shocks to impact volatility appeared to decline after the introduction of the Euro. Therefore, it can be deduced that the introduction of the Euro might have brought about a higher level of stability in global currency markets.

Chuang, Lu and Tswei (2007) investigated own shock transmission effects in six East Asian markets - Japan, Hong Kong, Singapore, South Korea, Taiwan and Thailand. The study employed a VAR-BEKK framework for empirical analysis and weekly closing prices of the all share market indexes of these six markets. Data was collected over a 15 year period. The major findings of this study were that the volatility responses of all East Asian markets to own shocks persist over considerably long periods.

Hammoudeh, Yuan and McAleer (2009) investigated shock transmission effects in the four countries of the Gulf Cooperation Council (GCC) - Kuwait, Qatar, Saudi Arabia and UAE. The study found sensitivity to own past shocks to be significant for all sectoral indexes in each country. The research also described transmission effects of own shocks at the individual market level succinctly: The Qatari market had the highest own shock transmission effects in the Service and Banking sectors. In Saudi Arabia, all sampled sectors had

equivalent own shock transmission effects. Moreover, in all four markets, volatility in the Industrial sector had the least sensitivity to own lagged shocks. On the other hand, volatility of the Banking sector was found to be the most sensitive to own past shocks.

Using daily sectoral data collected over duration of 33 months and a dynamic conditional correlation (DCC) MGARCH model, Righia and Cerreta (2012) investigated transmission effects of own shocks in the Financial Services and Consumer sectors of the Brazilian Stock Exchange. In both sectors, the study found evidence of persistence of own past shocks. However, own past shocks in the Consumer sector had a larger impact on volatility, as compared to those of the Financial sector. Mohammadi and Tan (2015) examined own shock transmission dynamics in the stock markets of U.S.A, Hong Kong and Mainland China (Shanghai and Shenzhen) over the 2 January 2001 to 8 February 2013 period. The study utilized a BEKK MGARCH model and found out that past shocks in each of these four markets had a significant effect on prevailing volatility. The USA market had the highest prevalence of own transmission effects of shocks, followed by the Shenzhen and Hong Kong markets respectively. On the other hand, own shock transmission effects were least evident in the Shanghai market.

Ogum, Beer and Nouyrigat (2015) fitted EGARCH models to all share index data from the Kenyan and Nigerian equity markets. This study found the asymmetric response to shocks coefficient in Nigeria to be negative, therefore implying that negative shocks caused higher volatility than positive shocks in this market. In Kenya though, inverted asymmetry effects were concluded to be present: the asymmetric volatility coefficient was positive and significant, thereby suggesting that positive shocks to the Kenyan equities market increase volatility more than negative shocks of an equal magnitude.

2.3.2 Cross Past Shocks and Volatility of Returns

Ewing (2002) argued that it is important for investors to comprehend the intrinsic linkages among different indexes of any economy before portfolio selection and allocation. Additionally, this study stated that the decision on whether to include securities from different sectors of the economy in a portfolio depends on a number of reasons including how, and to what extent, are various sectors related in terms of the tendency of shocks to spillover over from one sector to another. The study examined shock transmission patterns of five major sectors (Capital Goods, Financials, Industrials, Transport, and Utilities) of the US economy using S&P sectoral indexes, monthly data from 1988 to 1997 and a Generalized Forecast Error Variance Decomposition (GFEVD) methodology. The results found strong cross shock transmission linkages amongst the five indexes; and its major conclusion was that unanticipated shocks to each sector were readily impactful on the volatility of other sectors' returns.

Wang, Kutan, and Yang (2005) also used a GFEVD methodology and daily data for the 1994 - 2001 period to investigate the impact of information flows on sectoral returns within and across sectors of two stock exchanges (Shanghai and Shenzhen) in China. Their proposition was that information flows are tantamount to shock flows and market volatility is driven by arrival of new information, regardless of whether it is positive or negative. The study found out that in both exchanges, there was a high level of integration and sectoral prices reflected information from other sectors. Moreover, shocks to each stock exchange's Industry sector had the highest tendency to spillover thereby influencing the volatility of other sectors in both markets. Additionally, the Finance sector of the Shenzhen Stock Exchange was found to have the least tendency to transmit its shocks to other sectors, thereby implying a low level of integration with other sectors of this Exchange. This result is rather intriguing given the fact

that in most exchanges, the Finance sector is the one that tends to be quite interlinked with other sectors due to the fact that it provides capital to build these sectors. The general trend is for shocks to the Finance sector to be readily transmitted to other sectors.

Using an asymmetric Multivariate GARCH model, Kiani (2007) used size-weighted returns of the Jamaican Stock Exchange's sectors to appraise intra-market volatility spillovers. The study yielded evidence of a strong correlation between key sectors' volatilities with their lagged shocks, thereby implying the existence of cross transmission of shocks in these sectors. Moreover, the study found out that the asymmetric response to shocks effect in the Jamaican Stock Exchange was statistically insignificant thereby conjecturing that in this market, negative shocks do not necessarily result in higher levels of volatility than positive shocks of the same magnitude.

Al-Fayoumi, Khamees, and Al-Thuneibat (2009) used log-normalized daily returns over the Sep 2000 to Aug 2007 period and a Vector Error Correction (VECM) model to investigate multivariate cointegration and causal linkages of four - General, Financial, Industrial and Services - sectoral equity indexes of the Amman Stock Exchange in Jordan. One cointegrating vector was found in the four indexes. After fitting the VECM and running granger causality tests, results showed strong unidirectional granger causality effects from General, Financial, and Industry sectors to the Service sector. These results were triangulated with GFEVD as well as impulse response function (IRF) analyses and there was a concurrence of the outputs. The Financial sector was inferred to be the most influential sector in terms of shock transmission, while the Services sector had the least cross shock transmission linkages with other sectors. In was therefore inferred that of all sampled sectors, the Services sector offered the best opportunities for diversification.

Katzke (2014) investigated the dynamics of return co-movements between the six largest economic sectors in South Africa. The studied sectors were Financials, Industrials, Consumer Goods, Consumer Services, Telecommunications, and Basic Materials sectors. The study utilized Dynamic Conditional Correlation (DCC) and Asymmetric Dynamic Conditional Correlation (ADCC) MGARCH models for empirical analysis. Results yielded evidence of significant asymmetric response to shocks effects, with negative cross shocks being followed in all cases by higher levels of aggregate volatility *vis-a-vis* positive shocks. The results also suggest that periods of heightened uncertainty in global and domestic markets magnifies the comovement of returns between sectors of both types of markets and this undermines the ability of investors to diversify their portfolios.

Kalu and Ali (2015) examined domestic shock spillover effects between sectors of the Nigerian economy using a BEKK MGARCH methodology. The aim was to investigate the cross shock transmission effects between the Banking, Consumer Goods, and Shariah compliant sectors of the Nigerian Stock Exchange. Results indicated the presence of unidirectional transmission effects of shocks from the Banking sector to the Consumer Goods and Shariah compliant sectors. Moreover, there was evidence of bidirectional flows of shocks between the Consumer Goods and Shariah compliant sectors. The author concluded by noting that the study would have crucial implications to fund managers and financial risk managers since its findings would guide their portfolio selection and hedging strategies.

2.3.3 Own Past Volatility and Volatility of Returns

Worthington and Higgs (2004) investigated the transmission effects of own past volatility in value-weighted equity market indexes of nine major Asian countries - Hong Kong, Japan, Singapore, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand. The study

utilized weekly data for the 15 January 1988 to 6 October 2000 period; and the BEKK MGARCH model was employed in empirical analysis. Results showed that Singapore had the highest level of own volatility persistence while Hong Kong has the least level of own volatility transmission effects. Additionally, the study found out that on average, emerging economies (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) had a higher level of own volatility persistence as compared to developed economies (Hong Kong, Japan and Singapore). The conclusion was that the developed markets are more integrated with outside markets and hence their volatility is more driven by cross spillover effects, rather than by persistence of own volatility, when compared to developing countries. Therefore, the developed countries were inferred to be more susceptible to contagion flows from outside the region, as compared to developing countries.

Using a multivariate GARCH model and daily returns data for the January 1, 1992 to June 6, 2005 period, Hassan and Malik (2007) investigated volatility transmission effects in the Dow Jones indexes of three US market sectors - Financial, Consumer, and Technology. All three sectors had significant levels of volatility persistence. Past own volatility was found to have the highest explanatory power for volatility in the Consumer sector, followed by the financial sector, while the IT sector had the least level of volatility persistence. Using univariate GARCH models and weekly sectoral data, Ijumba (2013) investigated the persistence of own volatility in the financial markets of the BRICS (Brazil, Russia, India, China and South Africa) countries. The study found out that past volatility had the highest explanatory power of volatility in China followed by Russia. On the other hand, the South African market exhibited the least level of persistence of volatility. The researcher however issued a caveat that ignoring structural breaks in the returns series could have led to overestimation of persistence of own volatility in some markets.

Mutai (2013) modeled persistence of own volatility in two large capitalization stocks of the Nairobi Securities Exchange – Safaricom PLC and Kenya Commercial Bank. The study utilized daily returns series for both stocks from 9th June 2008, to 31st December, 2010. Diagnostic testing revealed AR(1)-GARCH(1,1) and MA(2)-GARCH(1,1) models to be the optimum volatility models for Safaricom PLC and Kenya Commercial Bank respectively. Results of model fitting found the level of persistence of daily volatility for Safaricom to be 72.09% and 75.97% for Kenya Commercial Bank. The implication is that lagged volatility in these stocks has a slow rate of decay, and that the level of volatility in any given day informs the next day's volatility to a big extent.

Kalu and Ali (2015) investigated shock and volatility transmission effects within three sectors of the Nigerian Stock Exchange - the Banking, Consumer Goods and Shariah Compliant Equities sectors. The study utilized a BEKK MGARCH model and daily sectoral index returns for the 04 January 2010 to 30 April 2014 period, totaling to 1071 observations for each index. There was evidence of strong volatility persistence in all the three sampled sectors, with the consumer goods sector having the highest level of volatility persistence, followed by the Shariah compliant equities sector. Volatility persistence was least in the banking sector. This can be attributed to the fact that volatility in this sector is driven more by 'unexpected news' (shocks) than lagged volatility.

Majumder and Nag (2018) utilized an asymmetric BEKK-GARCH model to investigate volatility transmission patterns in sectors of the National Stock Exchange of India. The study was based on daily data for the January 2004 to January 2014 period for three sectoral indexes of this market - the Finance, FMCG, and IT sectors. There was evidence of statistically significant volatility persistence effects, with lagged volatility in the Finance

sector having the highest level of persistence, followed by the IT sector and finally the FMCG sector. Xiao and Dhesi (2010) examined own volatility transmission effects in four market indexes: three of these indexes were for the European market and one was for the USA market. These indexes were CAC (France), DAX (Germany), FTSE100 (Germany), and S&P500 (USA). The study fitted a BEKK MGARCH model and utilized daily closing prices of over the period 5th Jan, 2004 to 1st Oct, 2009. High levels of volatility persistence were present in all four indexes.

2.3.4 Cross Past Volatility and Volatility of Returns

Using data from two indexes of the London Stock Exchange, the FTSE250 large capitalization equity index and the FTSE Small Capitalization equity index, Harris and Pisedtasalasai (2005) investigated volatility spillover effects in this market. The research found out that transmission of shocks between the two indexes is bidirectional but volatility transmission between two indexes is unidirectional - from the FTSE250 large capitalization equity index and the FTSE Small Capitalization equity index.

Wang and Zivot (2006) used a DCC MGARCH model to investigate the prevalence of contagion effects between Thailand and the Chinese Economic Area (CEA) regional bloc during the Asian financial crisis of 1997 - 1998. The study compared the parameters of the DCC model for the pre crisis and post crisis periods. Results established that the post crisis period had significant levels of correlation between the two markets, thereby signifying the existence of contagion between these markets. Using a BEKK MGARCH model, Hassan and Malik (2007) investigated the shock and volatility transmission patterns in six sectors of the US economy. The results yielded evidence of highly persistent and statistically significant cross transmissions of volatility amongst all 15 pairs of the 6 sectors.

Hammoudeh, Yuan and McAleer (2009) examined volatility transmission trends in the United Arab Emirates (UAE)'s Abu Dhabi Securities Exchange. Using a BEKK-MGARCH(1,1) model for three market sectors (Service, Banking, and Insurance), this study yielded evidence of moderate bidirectional spillovers of volatility within all three sectors. Karmakar (2010) investigated volatility spillover patterns between large capitalization and small capitalization equities of the National Stock Exchange of India. The study utilized continuous (log transformed) daily returns data of the S&P CNX Nifty index (comprised of large capitalization equities) and CNX Nifty Junior index (comprised of small capitalization equities). Empirical analysis was undertaken using an asymmetric BEKK model. Results of model fitting yielded evidence of statistically significant bidirectional volatility spillover effects between the large capitalization and small capitalization equities.

Using a DCC MGARCH model and daily sectoral returns for the January 2, 2008 to September 30, 2010 period, Righia and Ceretta (2012) modeled variances and dynamic correlations of the firms listed in the Financial and Consumer sectors of the BM&F BOVESPA stock exchange in Sao Paulo, Brazil. This research yielded evidence of bidirectional transmission of volatility between the two sectors.

Salman *et al* (2013) investigated the spillover effects originating from the Banking sector to the Oil and Gas, Construction, Chemical, Food Producer, Fixed Line Telecommunication, Electricity and Personal Goods sectors of the Pakistan Stock Exchange. This study used daily data of 251 firms that are categorized under these eight sectors and the data collection period was January 2008 to December 2012. Weighted (by market share) sectoral returns were computed using market share data and daily prices of the sampled sectors' stocks. The study

utilized the BEKK MGARCH model for empirical analysis and yielded evidence that volatility in the banking sector tended to spillover to all other sampled sectors.

The volatility spillover relationship between the New York Stock Exchange (NYSE) and the Johannesburg Stock Exchange (JSE) was investigated by Yonis (2012). The study concluded the existence of persistent and statistically significant unidirectional volatility transmission from the NYSE to the JSE. De Camara (2013) investigated whether there was transmission of cross volatility to the FTSE All Share Index of the Johannesburg Stock Exchange (JSE) during three financial crises: the 1997 Asian financial crisis, the dotcom bubble of 2000-2001, and the global financial crisis of 2007–2008. The study found unidirectional volatility spillover effects arising from the originating market of each of these three crises to the JSE's FTSE All Share Index.

Chinzara and Aziakpono (2014) used univariate GARCH and multivariate Vector Autoregressive (VAR) models in investigating dynamic returns linkages and transmission of shocks and volatility between the South African market and the Australian, Chinese and American markets. Results of their study showed that statistically significant bidirectional transmission of volatility existed between the South African market and the Australian, Chinese and American markets. Using factor analysis, VAR models, multivariate GARCH models and daily data for the period 2000-2014, Kambadza and Chinzara (2014) analyzed the structure of returns volatility spillovers among the Kenyan and Mauritian stock markets. This study found evidence of a bidirectional volatility spillover effect between the Kenyan and Mauritian bourses.

Kuttu (2014) used a multivariate VAR-EGARCH model to investigate the dynamics of volatility transmission between thinly traded adjusted equities of the Ghanaian, Kenyan, Nigerian and South African securities markets. The study found the Nigerian market to be a major source of cross volatility that is transmitted to the Ghanaian, Kenyan, and South African markets. Uyaebo, Atoi and Usman (2015) used an ADCC MGARCH model to analyze volatility spillover dynamics of daily All Share Indexes in the equity markets of Nigeria, Kenya, United States, Germany, South Africa and China. The study utilized data for the February 14, 2000 to February 14, 2013 period. The results found the Nigerian and Kenyan markets to be most vulnerable to exogenous contagion flows. Moreover, this study also affirmed the absence of asymmetric response to shocks effects in the Nigerian and Kenyan stock markets, but confirmed their existence in other markets.

2.3.5 Moderating Effect of Liquidity

Sabri (2002) notes that higher levels of liquidity - that are endemic in highly integrated capital markets - tend to aggravate the rate of transmission of own shocks and volatility in such markets. Further, Xu, Taylor and Lu (2018) conclude that high liquidity is a key prerequisite factor for propagation of shock transmission in equity markets. Moreover, they note that the level of liquidity in U.S capital markets has an influence on the tendency of shocks and volatility in these markets to affect the volatility of other equity markets around the globe. This can be attributed to fact that the US economy is quite dominant in global commerce.

Baumöhl, Kočenda, Lyócsa and Výrost (2018) conjecture that the level of liquidity in any capital market tends to affect the ability of this market's shocks and volatility to spillover to other markets, thereby influencing their volatility in near future periods. The study observes

that markets with higher stock turnover ratios tend to propagate larger volatility spillovers to their interrelated counterparts, vis-à-vis markets with lower stock turnover ratios. Additionally, they note that excess liquidity - which is often evidenced by high stock turnover ratios - increases the susceptibility of a market to receipt of transmitted shocks and volatility shocks from other markets. The study concludes by stating that although highly liquid markets tend to propagate larger shocks to other markets, they are also susceptible to having large shocks getting transmitted to them from other markets.

2.4 Summary of Reviewed Literature and Research Gaps

The literature is quite rich with content on the subject matter of this research. Nevertheless, it contains some gaps that this study filled as its contribution to the body of knowledge. Therefore, the rationale for conducting the study was based on several key aspects, as follows:

First, most of the empirical literature is based in the developed countries/geopolitical regions. Due to the fact that securities markets in developing countries have started to gain the attention of global investors who are seeking diversification opportunities and local players who are keen on investing their surplus funds, it was imperative to investigate shock and volatility transmission patterns in the NSE.

Second, the fundamentals of security markets in emerging economies are quite distinct from those of the developed world. In the emerging markets for instance, there is prevalence of thinly traded counters, heavy concentration of the volume of daily trades in a few key stocks, and weak regulatory frameworks (Cheruiyot, 2017). These shortcomings invalidate the notion

that findings of past studies can be used to make inferences on shock and volatility transmission patterns of developing countries.

Thirdly, there is a shortage of studies in the literature on the tendency of market liquidity to moderate the rate of transmission of own past shocks and volatilities. Consequently, this study contributes to the body of knowledge and provides actionable recommendations that can influence policy as well as the decisions of market players, as far as the moderator and its relationship with the pertinent independent variables and the dependent variable is concerned.

Finally, previous authors mostly investigated the shock and volatility transmission effects between several distinct security markets, and seldom within distinct sectors of a single market. Of the ones who focussed on a single market, there was a tendency to investigate the shock and volatility transmission in only a few sectors (Hassan and Malik, 2007; Ahmed 2016; Kalu and Ali, 2015; Salman *et al.*, 2015). Few studies have comprehensively focused on the volatility dynamics of all sectors of an entire market. Conversely, this study was based on all sectors of the NSE in order to get a full picture on the effect of own & cross past shocks and own & cross past volatility on sectoral volatility in emerging markets.

2.5 Conceptual framework

A conceptual framework is a logical depiction of the interrelationships between the study variables as envisaged by the research. According to Myeko (2014), a conceptual framework illustrates the envisaged relationships between the variables of a study, thereby showing the propositions for hypothesis testing. The conceptual framework for the study is as per Figure 2.1.

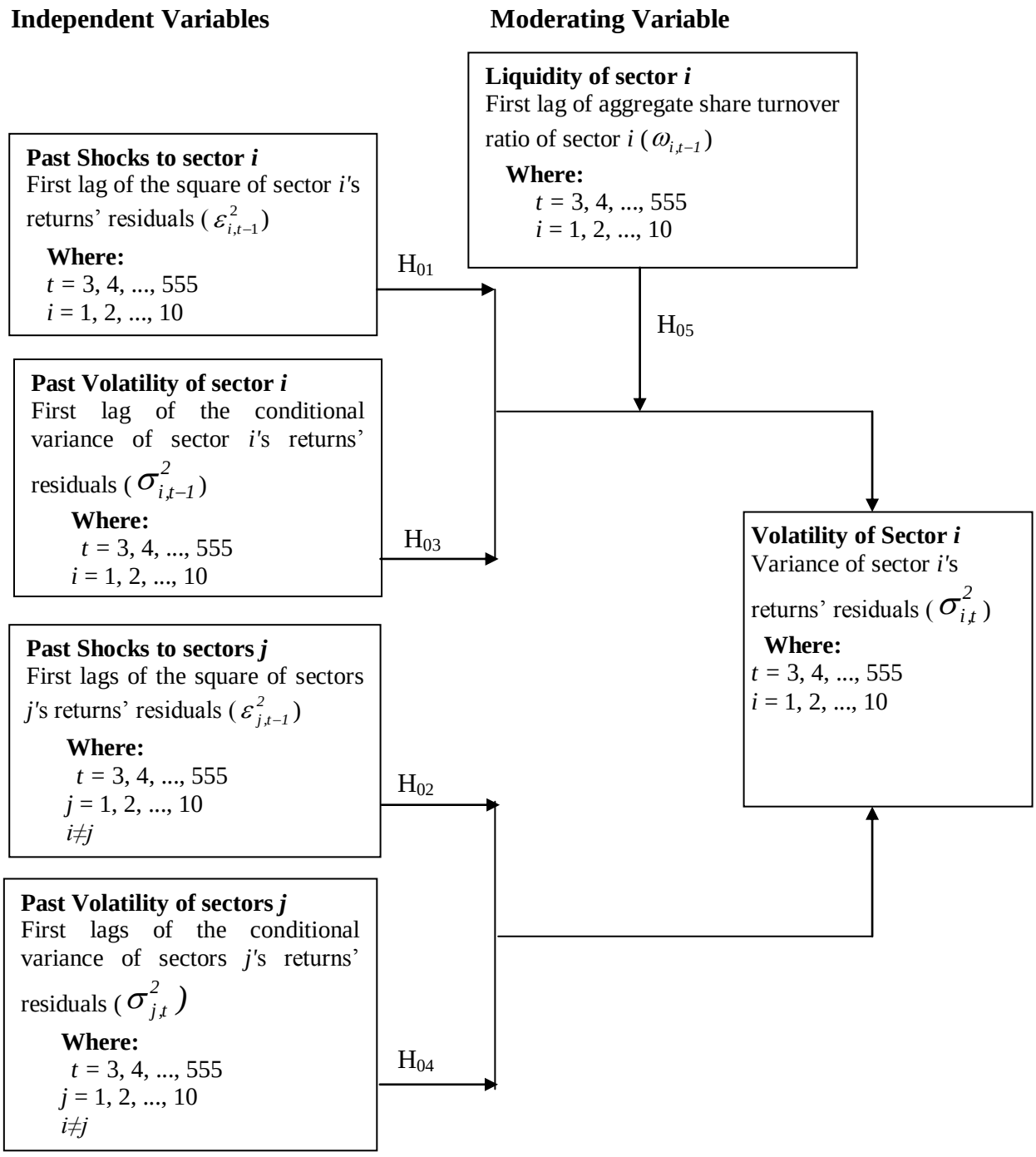

Figure 2.1: Conceptual Framework

Source: Researcher (2019)

As per Figure 2.1, the volatility of any NSE sector *i* , for any given week *t* , is influenced by: its own shocks from the previous week (*t-1*), its own persistent volatility from the previous week (*t-1*), shocks of the other nine sectors from the previous week (*t-1*), and persistent volatilities of the other nine sectors from the previous week (*t-1*). *i* is a random variable denoting any one sector of the NSE and *j* is a random variable representing the other nine sectors. Since the study was focused on 10 NSE sectors, the domain of *i* is $i=1,2,3,\ldots10$ and that of *j* is *j* is also $j=1,2,3,\ldots10$ for all $j\neq i$. This implies that when one sector is denoted as sector *i*, *j* will assume all values in the domain, except the one that has been assumed by *i* already.

The study also posits that the strength of the relationship between any given sector *i*'s own lagged shocks & own lagged volatility and its volatility is influenced by its level of lagged liquidity.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes how data was analyzed to yield empirical evidence on the subject matter of the study. The research philosophy is outlined first followed by the research design. The empirical models for data analysis are then articulated, followed by operationalization and measurement of variables. The target population and data collection procedure are then discussed next. Finally, the methodology that was utilized for empirical data analysis is elucidated.

3.2 Research Philosophy

Research philosophy is an innate belief about the way in which data pertinent to a phenomenon should be collected, analyzed and used. There are two major research philosophies in the social sciences: positivism and interpretivism (Saunders, Lewis and Thornhill, 2009). The positivism theory holds that there is stability of reality, such that it can be observed or described objectively; with no interference with the phenomenon being studied. This theory additionally holds that phenomena should be isolable and observations should be replicable. On the other hand, interpretive researchers assume that access to reality is only through social constructs such as language, consciousness, shared meanings, and instruments. Interpretivism as a philosophy arose from the critique of positivism in social sciences (Michaels, 2012).

This research was based on the positivist research philosophy because it was meant to establish the existence and properties of phenomena - a feat that was accomplished through testing of the study's hypotheses on the basis of results of empirical data analysis.

Additionally, the study favoured positivism since it aimed at investigating theoretical paradigms; and data was collected and analyzed to provide evidence needed to rebuff or reaffirm these theories. Best and Kahn (2006) argue for adoption of the positivist paradigm in instances where scientific processes are followed to validate hypothetical theories.

3.3 Research Design

Kothari (2004) defines research design as the overall strategy that a researcher chooses to integrate different components of a study in a coherent and logical way. This ensures that the research is undertaken in an effective and comprehensive manner. According to Sox & Greenfield (2009), research design constitutes the blueprint for collection, measurement, and analysis of data and reporting of results.

The causal research design was utilized to fulfil the objectives of this study. This design was deemed apt for the study since it enables the identification of the nature and magnitude of cause and effect relationships between independent variables and the dependent variable. According to Sox and Greenfield (2009), the causal design is useful in testing causality in time series analysis since it can yield evidence on the existence and nature of temporal dependences between time series variables. This facilitates the testing of causal-type hypotheses in time series analysis.

3.4 Empirical Model for Testing Hypotheses *i* to *iv*

The Baba, Engle, Kroner, Kraft (BEKK) Multivariate GARCH model of Engle and Kroner (1995) was used in this study to investigate shock and volatility transmission effects in line with the first four objectives of the study (models for testing hypothesis *v* are outlined in section 3.5). The BEKK MGARCH model is renowned for its flexibility and superiority in

investigating shock and volatility transmission effects as compared to other MGARCH models (Sheppard, 2003). Additionally, it is well suited for multivariate modelling of volatility due to its ability to detect shock and volatility transmission effects within the dynamic framework of multivariate time series (Kalu and Ali, 2015).

All GARCH-type models are usually fitted in two steps, as pioneered by Bollerslev (1986): The first step is to fit the mean equation while the second step is estimation of the variance equation. This two-step approach is necessary since the gist of such analyses is to model the variance of the mean equation's residuals in step two. Therefore, the mean equation must first be fitted to extract these residuals.

Before any models could be fitted, the 554 weekly observations of the 10 sectors' returns had to be determined first. The section below describes how the returns of each sector were computed.

3.4.1 Determining the Return of a Sector

This study mainly relied on weekly capitalization-weighted sectoral returns data for empirical analysis. Antonakakis (2008) notes that capitalization weighted sectoral returns take into account the relative importance of individual stocks in a sector. Therefore, sectoral returns that are computed using this weighting method tend to have long term stability and results that are based on them have a high level of face validity.

Before compiling the capitalization weighted returns for the sampled sectors, it was imperative to first compute a capitalization weighted index for each of them. Sharpe, Alexander and Bailey (2006) define a capitalization weighted index as a stock market index

whose components are weighted according to the total market value of their outstanding shares. There were 10 sectors with firms that traded consistently over the 6th June 2008 and 8th February 2019 period, and hence 10 capitalization weighted indexes had to be computed.

Following Jordan, Miller and Dolvin (2012), the value of the capitalization-weighted index $\psi_{i,t}$ of sector *i* for any given week, *t* was computed as per Equation 3.1 below:

$$\psi_{i,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}} \tag{3.1}$$

Where:

- $P_{s,t}$ is closing price of stock *s*, one of the constituents of sector *i*, as at end of week *t*
- $CAP_{s,t}$ is market capitalization of stock *s*, one of the constituents of sector *i*, as at end of week *t*
- *n* is the number of stocks that are listed under sector *i*
- *i* = 1,2,…,10 sectors
- *t* = 1, 3, ..., 555 weeks

For each sector, in every week, the share prices of individual component stocks are expected to change, thereby leading to changes in the overall index. The impact that changes in the individual stocks' prices have on the overall sectoral index is proportional to each stock's market capitalization (share price multiplied by number of outstanding shares).

After computing a market capitalization weighted index for each sector, the weekly sectoral returns were computed as a ratio of the capital gain realized over a particular week by the sectoral index to the value of the sectoral index at the beginning of the week (Jordan, Miller & Dolvin, 2012). Since one degree of freedom was lost in computing the market capitalization weighted sectoral indexes, each of the 10 sectoral indexes had 554 observations, i.e. for weeks 2,3, …, 555. This is as per Equation 3.2 below:

$$R_{i,t} = \frac{(\psi_{i,t} - \psi_{i,t-1})}{\psi_{i,t-1}} \tag{3.2}$$

Where:

- $R_{i,t}$ is the return of sector i for week t
- $\psi_{i,t}$ is closing value of sector i's index as at end of week t
- $\psi_{i,t-1}$ is closing value of stock i's index as at end of week t-1.
- i = 1,2,…,10 sectors
- t = 2, 3, ..., 555 weeks

3.4.2 Stage One of Multivariate Analysis: Mean Equation Fitting

In stage one of BEKK MGARCH analysis, the mean equation, which is a vector autoregressive (VAR(1)) model of order one for the returns as at any given time t of the NSE's 10 sectors was fitted. The mean equation was fitted at a single lag, since this was the lag order that was selected optimally via the consensus of four information criteria: the prediction error (FPE), the Akaike information Criterion (AIC), the Schwarz Bayesian information criterion (SBIC) and the Hanna Quinn Information criterion (HQIC). The model for the mean equation was as per Equation 3.3 below:

$$R_t = \alpha + \theta' R_{t-1} + \varepsilon_t \tag{3.3}$$

Where:

- t = 3, 4, ..., 555 weeks
- R_t is a *10X1* vector of the estimated returns of the 10 sectors of the NSE as at time *t*. This is as per Equation 3.4 below.

$$R_t = \begin{bmatrix} R_{1,t} \\ R_{2,t} \\ \vdots \\ R_{9,t} \\ R_{10,t} \end{bmatrix}, \tag{3.4}$$

- α is a *10X1* vector of intercept (long term drift) coefficients. This is illustrated in Equation 3.5

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_9 \\ \alpha_{10} \end{bmatrix} \tag{3.5}$$

- θ' is a *10X10* matrix of return spillover coefficients. Matrix θ' is elucidated in Equation 3.6 below.

$$\theta' = \begin{bmatrix} \theta_{11} & \theta_{21} & \cdots & \theta_{91} & \theta_{101} \\ \theta_{12,} & \theta_{22} & \cdots & \theta_{92} & \theta_{102} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \theta_{19} & \theta_{29} & \cdots & \theta_{99} & \theta_{109} \\ \theta_{110} & \theta_{210} & \cdots & \theta_{910} & \theta_{1010} \end{bmatrix} \quad (3.6)$$

The diagonal coefficients of matrix θ' measure the own return spillover effects. For each sector, this is the extent to which the returns that are realized in any given week are influenced by its own returns of the previous week. The off diagonal coefficients measure the cross return spillover effects. This effect is manifested when the returns of some sectors for any given week spillover/affect the returns of other interlinked sectors in the following week (Lee, Naranio, and Simans, 2014).

- R_{t-1}, as indicated in Equation 3.7, is a *10X1* vector of single lagged returns of the NSE's 10 sectors.

$$R_{t-1} = \begin{bmatrix} R_{1,t-1} \\ R_{2,t-1} \\ \vdots \\ R_{9,t-1} \\ R_{10,t-1} \end{bmatrix} \quad (3.7)$$

- ε_t is a *10X1* vector of residuals which follows a multivariate normal distribution with a mean of 0 and a covariance-variance matrix H_t. Therefore, $\varepsilon_t \sim N(0, H_t)$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{9,t} \\ \varepsilon_{10t} \end{bmatrix} \tag{3.8}$$

3.4.3 Stage Two of Multivariate: Variance Equation Fitting

In stage two, the model for the covariance-variance matrix of the vector of residuals (ε_t) was fitted, using the BEKK MGARCH model specification and its coefficient matrices estimated. Since a lag length of one yields the most parsimonious specification for multivariate GARCH models (Mohammadi and Tan, 2015; Mootamri, 2011; Bauwens *et al*, 2006), this research utilized a single lag for both ARCH terms and GARCH terms of the BEKK MGARCH model. The study was particularly interested in the coefficients of matrices ***A***, and ***B*** since their significance and magnitude formed the basis for testing the first four hypotheses.

The BEKK MGARCH model was specified as per Equation 3.9.

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{3.9}$$

Where:

- H_t is a *10X10* variance-covariance matrix. As shown in Equation 3.10, the volatilities (as at the end of any given week, *t*) of the 10 sectors of the NSE appear along the main diagonal of this matrix.

$$H_t = \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} & \cdots & \sigma_{19,t} & \sigma_{110,t} \\ \sigma_{21,t} & \sigma_{2,t}^2 & \cdots & \sigma_{29,t} & \sigma_{210,t} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \sigma_{91,t} & \sigma_{92,t} & \cdots & \sigma_{9,t}^2 & \sigma_{910,t} \\ \sigma_{101,t} & \sigma_{102,t} & \cdots & \sigma_{109,t} & \sigma_{10,t}^2 \end{bmatrix} \tag{3.10}$$

- *C* is an upper triangular matrix of intercept coefficients. The diagonal coefficients of Matrix *C* are drift constants for the volatility processes of the NSE's sectors, while the off-diagonal coefficients are the drift constants for the covolatility processes. The components of matrix *C* are elucidated in Equation 3.11 below:

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{19} & c_{110} \\ & c_{22} & \cdots & c_{29} & c_{210} \\ & & \ddots & \vdots & \vdots \\ & & & c_{99} & c_{910} \\ & & & & c_{1010} \end{bmatrix} \tag{3.11}$$

- *C'* is the transpose of matrix *C*.

- *A*, as specified in Equation 3.12, is a *10x10* matrix of coefficients. The coefficients of matrix *A* measured the extent to which the level of volatility in the NSE's sectors in any

given week, *t* can be attributed to the shocks that impacted these sectors in the previous week. The diagonal coefficients of matrix *A* quantified own transmission of shocks effects (the effect of the respective sectors' own shocks from the last week on their volatilities) while its off-diagonal coefficients evaluated cross spillover of shocks effects (the effect of other sectors' shocks from the last week on each sector's volatility).

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{19} & a_{110} \\ a_{21,} & a_{22} & \cdots & a_{29} & a_{210} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{91} & a_{92} & \cdots & a_{99} & a_{910} \\ a_{101} & a_{102} & \cdots & a_{109} & a_{1010} \end{bmatrix} \quad (3.12)$$

- A' is the transpose of matrix *A*

- ε_{t-1} , *as* shown in Equation 3.13, is a *10X1* vector of residuals at time *t-1*. The squares of the elements of this vector measured the shocks of the 10 sectors of the NSE for the previous week, *t-1*.

$$\varepsilon_{t-1}=\begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \vdots \\ \varepsilon_{9,t-1} \\ \varepsilon_{10,t-1} \end{bmatrix} \quad (3.13)$$

- ε'_{t-1} is the transpose of vector ε_{t-1}

- *B* as indicated in Equation 3.14 is a *10x10* coefficient matrix. The diagonal coefficients of matrix *B* showed the extent to which each sector's volatility in any given week is affected by its own level in the previous week (persistence of own volatility). The off diagonal coefficients evaluated the effect of other sectors' volatilities in any week on the volatility of each sector in the following week (persistence of contagion effects).

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{19} & b_{110} \\ b_{21,} & b_{22} & \cdots & b_{29} & b_{210} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ b_{91} & b_{92} & \cdots & b_{99} & b_{910} \\ b_{101} & b_{102} & \cdots & b_{109} & b_{1010} \end{bmatrix} \tag{3.14}$$

- B' is the transpose of matrix *B*
- H_{t-1} is a *10x10* matrix of variances and covariances at time *t-1*. Its diagonal elements indicate the first lag of the volatilities of the *10* NSE sectors.

$$H_{t-1} = \begin{bmatrix} \sigma^2_{1,t-1} & \sigma_{12,t-1} & \cdots & \sigma_{19,t-1} & \sigma_{110,t-1} \\ \sigma_{21,t-1} & \sigma^2_{2,t-1} & \cdots & \sigma_{29,t-1} & \sigma_{210,t-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \sigma_{91,t-1} & \sigma_{92,t-1} & \cdots & \sigma^2_{9,t-1} & \sigma_{910,t-1} \\ \sigma_{101,t-1} & \sigma_{102,t-1} & \cdots & \sigma_{109,t-1} & \sigma^2_{10,t-1} \end{bmatrix} \tag{3.15}$$

3.5 Empirical Models for Testing Hypothesis *v*

In order to test for the moderating effect of liquidity on the relationship between own past shocks & own past volatility and current volatility, the study utilized the two step methodology proposed by Irwin and McClelland (2001). This process is described in sections 3.5.1 and 3.5.2.

3.5.1 Step One of Testing the Moderating Effect of Liquidity

In step one, 10 base models for testing the moderating effect of liquidity were estimated using the univariate GARCH (1,1) model specification. Equation 3.17, which is a GARCH (1,1) model, was used to estimate the volatility of each NSE sector as a function of its past own shocks and past own volatility from the previous week. Before fitting Equation 3.17, the study first fitted the mean equation (Equation 3.16) which is a first order autoregressive (AR(1)) model of sectoral returns. The mean equation was fitted to facilitate extraction of the $\varepsilon_{i,t}$ residuals; since Equation 3.17 entailed estimation of the variance of these residuals as a function of a single lag of their squares and a single lag of their variance.

$$R_{i,t} = cm_i + f_i R_{i,t-1} + \varepsilon_{i,t} \tag{3.16}$$

$$\sigma^2_{i,t} = cv_i + \alpha_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_{i,t-1} \tag{3.17}$$

Where:

- $R_{i,t}$ is the return of sector *i* for week *t*
- cm_i is the intercept of the univariate mean equation for sector *i*
- f_i is the coefficient of $R_{i,t-1}$
- $R_{i,t-1}$ is a single lag of $R_{i,t}$, and is the regressor of the univariate AR(1) mean equation.

- $\varepsilon_{i,t}$ is the residual of the mean equation. $\varepsilon_{i,t}$ is a white noise process that follows a normal distribution with a mean of zero and a definite variance $\sigma_{i,t}^2$. Thus, $\varepsilon_{i,t} \sim N(0,\sigma_{i,t}^2)$
- $\sigma_{i,t}^2$ is the volatility of sector *i* 's returns at week *t*
- cv_i is the intercept coefficient of the univariate GARCH(1,1) variance equation for sector *i*
- α_i is the coefficient of $\varepsilon_{i,t-1}^2$
- $\varepsilon_{i,t-1}^2$ is the first lag of the square of $\varepsilon_{i,t}$, the residual of mean equation. It represents the previous week's shocks to sector *i* that influence its volatility in the present week.
- γ_i is the coefficient of $\sigma_{i,t-1}^2$
- $\sigma_{i,t-1}^2$ is the first lag of the volatility of sector *i* 's returns at week *t* . It represents the previous week's volatility which remains persistent such that it influences the present week's volatility.
- *i* = 1,2,…,10 sectors
- *t* = 3, 4, ..., 555 weeks

3.5.2 Step Two of Testing the Moderating Effect of Liquidity

In the second step, each of the 10 GARCH (1,1) models fitted above was extended with three additional exogenous regressors for the variance equation: the moderating variable and two interaction terms. This was in accordance with Cohen *et al.* (2003) who propose that an interaction model to test for a moderating effect should include the base regressors, the moderating variable, as well as interaction terms that are created as products of the moderating variable and the base regressors.

Before the interaction models for testing the moderating effect of liquidity were fitted, the liquidity variables of the NSE's 10 sectors and the interaction terms were computed as per the elucidation below.

3.5.2.1 Determining the Liquidity of a Sector

The study measured liquidity using the aggregate weekly stock turnover ratio that was developed by Lo and Wang (2000). This metric measures liquidity for a particular market sector, *i* as the total number of shares of sector *i* 's firms that are traded over a particular week, *t* divided by the total number of shares outstanding for sector *i* 's firms in that period.

The aggregate weekly stock turnover ratio is computed as per Equation 3.18 below.

$$\omega_{i,t} = \frac{\sum_{d=1}^{5} \tau_{i\,d,t}}{\eta_{i,t}} \tag{3.18}$$

Where:

- $\omega_{i,t}$ is the liquidity of sector *i* for week *t*
- $\tau_{i\,d,t}$ is the number of total traded shares of sector *i* 's firms in day *d,* one of five trading days of week *t*
- $\eta_{i,t}$ is the number of total tradable shares of sector *i* 's firms as at end of week *t*
- *d* = 1,2,…,5 trading days in a single week *t*
- *i* = 1,2,…,10 sectors
- *t* = 3, 4, ..., 555 weeks

If a sector is highly liquid, the aggregate weekly stock turnover ratio will be high since there will be a plenty of bid and ask offers on stocks that are listed under it. On the other hand, an illiquid sector will have a low aggregate stock turnover ratio since the level of activity pertinent to shares that are listed under it is low.

3.5.2.2 Determining the Interaction Terms of a Sector

For each sector *i*, two interaction terms were computed as a product of the moderating variable and the two independent variables of the univariate GARCH (1,1) variance model (base model). The two interaction terms were denoted $IT_{si,t-1}$ and $IT_{vi,t-1}$.

$IT_{si,t-1}$ is the interaction term between the shock of the previous week and liquidity of the previous week for sector *i*. It was computed as per Equation 3.19 below:

$$IT_{si,t-1} = \varepsilon^2_{i,t-1} * \omega_{i,t-1} \tag{3.19}$$

Where:

- $\omega_{i,t-1}$ is the previous week's liquidity for sector *i*
- $\varepsilon^2_{i,t-1}$ is the shock of the previous week for sector *i*
- $i = 1,2,\ldots,10$ sectors
- $t = 3, 4, \ldots, 555$ weeks

On the other hand, $IT_{vi,t-1}$ is the interaction term between volatility of the previous week and liquidity of the previous week for sector *i*. This interaction term was computed as per Equation 3.20 below.

$$IT_{vi,t-1} = \sigma^2_{i,t-1} * \omega_{i,t-1} \quad (3.20)$$

Where:

- $\omega_{i,t-1}$ is the previous week's liquidity for sector *i*
- $\sigma^2_{i,t-1}$ is the volatility of sector *i* in the previous week
- $i = 1,2,\ldots,10$ sectors
- $t = 3, 4, ..., 555$ weeks

3.5.2.3 Fitting the Interaction Models

After determining the liquidity variable and interaction terms, the interaction models for all 10 NSE sectors were estimated. The mean equations were estimated as per Equation 3.21 while the variance equations were fitted with three exogenous regressors each, as per Equation 3.22

$$R_{i,t} = cm_i + f_i R_{i,t-1} + \varepsilon_{i,t} \quad (3.21)$$

$$\sigma^2_{i,t} = cv_i + \alpha_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_{i,t-1} + \nu_i \omega_{i,t-1} + \lambda_i IT_{si,t-1} + \phi_i IT_{vi,t-1} \quad (3.22)$$

Where:

- $R_{i,t}$ is the return of sector *i* for week *t*
- cm_i is the intercept parameter of the univariate AR(1) mean equation for sector *i*
- f_i is the coefficient of $R_{i,t-1}$
- $R_{i,t-1}$ is a single lag of $R_{i,t}$, and is the regressor of the univariate mean equation.
- $\varepsilon_{i,t}$ is the residual of the mean equation. $\varepsilon_{i,t}$ is a white noise process that follows a normal distribution with a mean of zero and a definite variance $\sigma_{i,t}^2$, i.e. $\varepsilon_{i,t} \sim N(0,\sigma_{i,t}^2)$
- $\sigma_{i,t}^2$ is the volatility of sector *i* 's returns at week *t*
- cv_i is the intercept parameter of the univariate variance equation for sector *i*
- α_i is the coefficient of $\varepsilon_{i,t-1}^2$
- $\varepsilon_{i,t-1}^2$ is the first lag of the square of $\varepsilon_{i,t}$, the residual of mean equation. It represents the previous week's shocks to sector *i* that influence its volatility in the present week.
- γ_i is the coefficient of $\sigma_{i,t-1}^2$
- $\sigma_{i,t-1}^2$ is the first lag of the volatility of sector *i* 's returns at week *t* . It represents the previous week's volatility which remains persistent such that it influences the present week's volatility.
- ν_i is the coefficient of $\omega_{i,t-1}$
- $\omega_{i,t-1}$ is the previous week's liquidity for sector *i*
- λ_i is the coefficient of $IT_{si,t-1}$
- $IT_{si,t-1}$ is the interaction term between the shock of the previous week and liquidity of the previous week for sector *i*.

- ϕ_i is the coefficient of $IT_{vi,t-1}$
- $IT_{vi,t-1}$ is the interaction term between volatility of the previous week and liquidity of the previous week for sector *i*.
- i = 1,2,…,10 sectors
- t = 3, 4, ..., 555 weeks

Following the Helm and Mark (2012) criteria, it would be inferred that liquidity has moderation effects on the relationship between own past shocks & volatility and current volatility if coefficients λ_i and ϕ_i are statistically significant. This implies that the two interaction terms, and therefore liquidity, in any given week have a significant effect on the level of volatility in the succeeding week. Alternatively, the moderating effect of liquidity would be deemed to be significant in any sector that had a higher R^2 for the interaction model *vis-à-vis* the base model.

3.6 Operationalization and Measurement of Variables

The study sought to investigate how past shocks and past volatility influences the volatility of sectoral returns in the Nairobi Securities Exchange, and how the level of sectoral liquidity moderates the effect of own past shocks & volatility on current volatility in each NSE sector.

It is noteworthy that the independent and dependent variables for all variance equations are latent. According to Tabachnick and Fidell (2001), latent variables cannot be directly observed and so they must be inferred from other variables which are observable. Therefore, in the study, the independent and dependent variables for variance equations were inferred from the observed weekly returns of the NSE's 10 sectors that were sampled.

However, variables of the mean equations weren't latent since their input data was simply the first lag of raw sectoral returns observations. Furthermore, the moderating variable (first lag of sectoral liquidity) also wasn't latent because it was directly computed as the first lag of the aggregate weekly stock turnover ratio.

The variables were operationalized as per Table 3.1.

Table 3.1: Operationalization and Measurement of Variables

Type	Variable	Operationalization	Measurement	Hypothesized Direction
Variance Equations				
Independent Variable	Own past shocks	Shocks that impacted the returns of sector *i* in week *t-1*	$\varepsilon^2_{i,t-1}$ (first lag of the square of the residuals of sector *i*'s current returns) *i = 1,2,...,10 sectors: t = 3, 4, ..., 555 weeks*	Positive
Independent Variable	Cross past shocks	Shocks that impacted returns of the NSE's other 9 sectors in week *t-1*	$\varepsilon^2_{j,t-1}$ (first lag of the square of the residuals of current returns for other 9 sectors (excluding sector *i*) *j = 1,2,...,10 sectors: j ≠ i* *t = 3, 4, ..., 555 weeks*	Positive
Independent Variable	Own past volatility	Conditional volatility of the returns of sector *i* for week *t-1*	$\sigma^2_{i,t-1}$ (first lag of the conditional variance of the residuals of sector *i*'s current returns) *i= 1,2,...,10 sectors: t = 3, 4, ..., 555 weeks*	Positive
Independent Variable	Cross past volatilities	Conditional volatilities of the returns of the NSE's other 9 sectors for week *t-1*	$\sigma^2_{j,t-1}$ (first lag of the conditional variance of the residuals of current returns for other 9 sectors(excluding sector *i)*) *j = 1,2,...,10 sectors: j ≠ i* *t = 3, 4, ..., 555 weeks*	Positive
Dependent Variable	Volatility	Volatility of the returns of sector *i* for week *t*.	$\sigma^2_{i,t}$ (conditional variance of the residuals of sector *i*'s current returns) *i = 1,2,...,10 sectors: t = 3, 4, ..., 555 weeks*	None
Moderating Variable				
Moderating Variable	Liquidity	Liquidity of sector *i* for week *t-1*	$\omega_{i,t-1} = \frac{\sum_{d=1}^{5} \tau_{id,t-1}}{\eta_{i,t-1}}$ (first lag of sector *i*'s current aggregate weekly stock turnover ratio) *i = 1,2,...,10 sectors: t = 3, 4, ..., 555 weeks*	Positive

Source: Researcher (2019)

3.7 Target Population

For this study, the target population was the sectors of the NSE. The NSE had 13 sectors, with 66 firms listed under them, as at February 2019. Table 3.2 shows these sectors and the

number of firms that are listed under each (the actual firms that are listed under each of the 13 sectors are shown in Appendix I).

Table 3.2: Target Population

	Sector	Number of Listed Firms	Percentage
1.	Agricultural	7	10.61%
2.	Automobiles & Accessories	1	1.52%
3.	Banking	12	18.18%
4.	Commercial & Services	12	18.18%
5.	Construction & Allied	5	7.58%
6.	Energy & Petroleum	5	7.58%
7.	Insurance	6	9.09%
8.	Investment	5	7.58%
9.	Investment Services	1	1.52%
10.	Manufacturing & Allied	9	13.64%
11.	Telecommunications & Technology	1	1.52%
12.	Real Estate Investment Trust	1	1.52%
13.	Exchange Traded Fund	1	1.52%
Total		**66**	**100.00%**

Source: Nairobi Securities Exchange (2019)

The Commercial & Services and Banking sectors account for the majority of these firms (18.18%). These are followed by the Manufacturing & Allied sector (13.64%) and the Agricultural sector (10.61%) respectively. On the other hand, each of the following sectors

contain only 1.52% of NSE listed firms: Automobiles & Accessories, Investment Services, Telecommunications & Technology, Real Estate Investment Trust, and Exchange Traded Fund.

3.8 Sample and Sampling Design

According to Mugenda and Mugenda (2003), a census should be conducted when the population is small and data can be realistically collected from all the elements of a study's population. Since the target population was 13 market sectors, the census approach was utilized in this study. The criterion for inclusion in the sample was availability of data. Therefore, only sectors for which complete data was available over the data collection period (6th June 2008 to 8th February 2019) were included. Sectors with no listed stocks at any point over the data collection period were excluded from the sample. Additionally, the data for stocks that weren't listed before 6th June 2008, were delisted before 8th February 2019, or didn't trade at any time over the data collection period was expunged. Consequently, 3 entire sectors and 21 individual stocks were dropped since they didn't meet the criteria for inclusion in the sample.

Ultimately, the study utilized a sample of 10 sectors, with 45 firms listed under them. The sectors that comprised the study's sample, together with the stocks which were actively traded under each sector over the study period, are summarized in Table 3.3. The actual qualifying firms that are listed under each of the sampled 10 sectors are shown in Appendix II.

Table 3.3 Study Sample

Sector	Number of Listed Firms	Percentage
1. Agricultural	6	13.33%
2. Automobiles & Accessories	1	2.22%
3. Banking	9	20.00%
4. Commercial & Services	8	17.78%
5. Construction & Allied	5	11.11%
6. Energy & Petroleum	3	6.67%
7. Insurance	3	6.67%
8. Investment	2	4.44%
9. Manufacturing & Allied	7	15.56%
10. Telecommunications & Technology	1	2.22%
Total	**45**	**100%**

Source: Study Data (2019)

The Banking sector accounted for the largest proportion (20%) of firms that met the criteria for inclusion in the study's sample. It was followed by the Commercial & Services (17.78%) and then the Manufacturing & Allied sector (15.56%). On the other hand, firms listed under both Telecommunications & Technology and Automobiles & Accessories sectors accounted for only 2.22% of the total number of firms that met the inclusion criteria.

3.9 Data Collection Procedure

The study's data was procured from the Nairobi Securities Exchange in the form of daily trading reports. From these reports, secondary time series data on the weekly closing prices and market capitalization for the 45 equities that traded consistently over the data collection period was collated using Data Entry Sheet 1 (Appendix IV(a)).

Moreover, daily data on traded volume and number of tradable shares outstanding - which was required for testing hypothesis *v* of the study - was collated for the 45 selected equities using Data Entry Sheet 2 (Appendix IV(b)).

After its procurement and collation, data was then compiled, as per the Document Review Guides III and IV (Appendices V(a) and V(b)), in readiness for analysis. The result of data compilation and preparation was 10 time series of weekly sectoral returns, 10 time series of weekly sectoral liquidity, and 20 weekly time series of the interaction terms. The sectoral indexes data was for the 6th June 2008 to 8th February 2019 period - a length of 555 weeks. One degree of freedom was lost after computing the sectoral returns and consequently, the returns data was for 554 weeks - the 13th June 2008 to 8th February 2019 period. On model fitting, one more degree of freedom was lost since all analysis was conducted at a single lag. Therefore, all empirical models that were fitted in this study used data for the 20st June 2008 to 8th February 2019 period – a total of 553 observations.

According to Gomes and Chaibi (2015), time series data with at least 500 observations is adequate for application in both univariate and multivariate GARCH analysis. The weekly frequency was chosen since weekly data averts the potential effects of excessive noise and day-of-the-week effect that characterize daily data while curtailing the loss of degrees of

freedom that occurs in low frequency data, such as monthly or annual data (Ebrahim, 2000). Moreover, analysis was conducted at the sectoral level since this helped in evaluating the aggregate shock and volatility transmission patterns for the entire market. Utilization of sectoral data precluded the problem of extreme dimensionality that could arise if analysis was done at the individual stock level (Bauwens *et al*., 2006). Furthermore, the NSE has witnessed a departure from focusing on single stocks. For instance, the recently introduced Exchange Traded Funds (such as the FTSE 15 and FTSE 25) that are robust for idiosyncratic risk are gaining prominence day after day (Cytonn, 2018).

3.10 Data Analysis

Data was analyzed using descriptive statistics, trend analysis, and both multivariate and univariate GARCH models. The first four objectives of the study were evaluated using a VAR(1)BEKK-MGARCH(1,1) model while univariate GARCH (1,1) models and univariate GARCH (1,1) models with exogenous variance regressors were used to accomplish the fifth objective of this study. The *WinRATS* Version 10 software package was utilized for empirical analysis.

3.10.1 Descriptive Statistics

Before fitting the empirical models, descriptive statistics of the raw data were computed so as to depict its general outlook. In particular, the mean, minimum, maximum, standard deviation, skewness and kurtosis were computed and discussed. After discussion of descriptive statistics, the relevant empirical models were utilized to yield results for testing the study's hypotheses.

3.10.2 Trend Analysis

The study used time plots to depict the variability of the raw data over the measurement period. This was essential since it indicated the patterns of the various time series variables over time, outlining their joint communalities as well as the unique attributes of each.

3.10.3 Empirical Model Fitting

This section describes the processes that were used in fitting the empirical models of data analysis in the study.

3.10.3.1 Diagnostic Tests

Diagnostic tests are procedures that are undertaken to prevent misspecification of econometric models. Misspecification tends to distort the sampling properties of estimated parameters, such as their standard errors and confidence intervals, and this can result in making of wrongful inferences due to hypothesis testing errors. Misspecification also has adverse implications for any inferences that might be based on the fitted model, including forecasting. Therefore, it is absolutely essential to ensure that the assumptions which have been posited about the functional form of an econometric model and the distribution of its residuals are met before estimation (Harris and Pisedtasalasai, 2005).

Bauwens *et al* (2006) note that there are four conditions that must be met to ensure that parameters of GARCH-type models are unbiased and efficient: Firstly, the time series variables used in the mean equation must be stationary. Secondly, in the case of multivariate GARCH models, the mean equation should be fitted using the appropriate model - A Vector Error Correction (VEC) specification should be utilized for the mean equation in case the variables are not stationary and are cointegrated, while a VAR mean equation model ought to

be fitted if the variables are stationary at levels. Thirdly, ARCH effects must be present in the squared residuals of the mean model. Finally, the standardized residuals of the GARCH model must not exhibit any autocorrelation but should be white noise processes with a mean of zero and a variance of one. To check for - and ensure - conformance with these conditions, the study undertook the following diagnostic testing procedures:

Testing for Stationarity - Stationarity is a key requirement for analysis of time series data. According to Wang and Tsay (2013), a stationary time series is one which is time independent and therefore its statistical properties such as variance, mean, and autocorrelation do not change when the time period under consideration is shifted. Data that is not stationary usually yields spurious results thereby increasing the probability of making errors in hypothesis testing. The Augmented Dickey–Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were used to test for stationarity in the raw returns data. The ADF test is based on the null hypothesis that a time series variable has a unit root against an alternative hypothesis that the variable is stationary at levels (Fuller, 1976). On the other hand, the KPSS test utilizes a null hypothesis of stationarity against the alternative hypothesis that a unit root is present (Kwiatkowski, Phillips, Schmidt and Shin, 1992). The ADF and KPSS tests confirmed that all the time series variables of this study were stationary at levels.

Testing for stationarity was a critical juncture in the multivariate GARCH analysis part of this study because it guided selection of the appropriate functional form of the BEKK MGARCH model. Since all returns series were stationary at levels, it was consequently deduced that they had no cointegrating relations. This is due to the fact that by definition, cointegration can only exist in a system of non stationary time series variables that have the same order of integration and can be linear combined into another time series which is stationary at levels

(Johansen, 1995). Consequently, the mean equation of the BEKK MGARCH variance model was fitted with level returns data as a VAR model.

Testing for ARCH Effects - ARCH (autoregressive conditional heteroscedasticity) effects is a statistical property that is deemed present in time series variables that exhibit autocorrelation in their squared residuals (Engle, 1982; Bollerslev, 1986, Brooks, 2008). The existence of ARCH effects in the mean equation must be verified first, before fitting any GARCH type model. The Hatemi-J and Hacker test is touted as the most robust way of testing for multivariate ARCH effects (Wang and Zivot, 2006), and therefore, it was utilized for that purpose in this study. Additionally, the Engle LM test was utilized to test for ARCH effects with respect to the univariate models. Both the Hatemi-J & Hacker and Engle LM tests are based on the null hypothesis that there are no ARCH effects upto a specified number of lags (Hacker and Hatemi-J, 2005). All tests for ARCH effects that were undertaken in this study indicated the presence of these effects at the 5% level of significance, thereby giving the green light to fit GARCH-type models.

Testing for Residual Autocorrelation - In a correctly specified GARCH model, the standardized residuals of fitting the variance equation should not be autocorrelated. Instead, they should be identically and independently distributed with each standardized residual being a strong white noise process with a mean of zero and unit variance (Bollerslev, 1986). Ljung-Box Q tests were used to test for autocorrelation of the variance equations' residuals in this study, for all (multivariate and univariate) instances. The null hypothesis of the Ljung-Box Q test is that there is no autocorrelation of standardized residuals; upto a certain number of lags while the alternative hypothesis is that there is autocorrelation of standardized residuals, upto the same number of lags (Ljung and Box, 1978). For all Ljung-Box Q tests

that were undertaken in this study, the null hypothesis was not rejected, since the p values of these tests were not significant. Thus, the results of all Ljung-Box Q tests affirmed that the standardized residuals of all variance models did not exhibit any autocorrelation, but were following independent and identical white noise processes. Therefore, the models that were utilized in this study were deemed to have an apt goodness of fit.

3.10.3.2 Model Fitting

For the BEKK MGARCH model, the study used a VAR(1)BEKK-MGARCH(1,1) full model specification to yield results that were used to test the first four hypotheses of the study. Moreover, univariate AR(1)GARCH(1,1) models and univariate AR(1)GARCH(1,1) models with exogenous variance regressors were used to test hypothesis *v* of the study.

Finally, the results were discussed thereby laying the ground for making of conclusions, recommendations, and suggestions for future research.

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

4.1 Introduction

This chapter entails the analysis of data, reporting and discussion of results, and testing of the study's hypotheses. Prior to estimation of all volatility models, applicable diagnostic tests were undertaken. This was to assure conformance with the assumptions of fitting volatility models, thereby precluding the probability of making erroneous inferences when testing the hypotheses of the study.

4.2 Descriptive Statistics

In order to envisage a general picture of the raw data, descriptive analysis was undertaken. This involved computation of the mean, minimum, maximum, standard deviation, kurtosis, and skewness for sectoral indexes' weekly closing prices, sectoral indexes' weekly returns, and sectoral weekly liquidity. Table 4.1 shows the descriptive statistics for the weekly closing values of the NSE's 10 sectoral indexes while Table 4.2 indicates the descriptive statistics of the weekly returns of these indexes. Further, Table 4.3 illustrates the descriptive statistics on the NSE sectors' liquidity.

Table 4.1: Descriptive statistics of sectoral indexes' weekly closing values

Sector	Mean	Max	Min	S Dev.	Skewness	Kurtosis
Agricultural	923.55	1844.95	403.28	391.01	0.51	2.24
Automobiles & Accessories	46.07	78.25	29.30	10.95	0.56	2.43
Banking	629.04	1082.46	268.51	217.23	0.26	2.07
Commercial & Services	306.98	529.06	144.40	102.12	0.46	2.20
Construction & Allied	321.49	454.67	220.85	55.28	0.29	2.09
Energy & Petroleum	36.87	56.23	23.70	7.05	0.37	2.62
Insurance	344.47	659.68	79.86	189.88	0.08	1.32
Investment	34.70	75.05	14.70	15.01	0.64	2.52
Manufacturing & Allied	436.94	691.80	276.72	95.71	0.39	2.30
Telecommunications & Technology	11.75	32.25	2.55	8.37	0.67	2.19

Source: Study Data (2019)

As evident in Table 4.1, the Agricultural sector's index has the highest mean for the weekly closing values while the Telecommunications & Technology sector's index has the least mean. Moreover, the Agricultural sector index also has the largest maximum closing values and the largest minimum closing value while the Telecommunications & Technology sector has the least maximum value and also the least minimum value. This trend continues even with respect to the standard deviation. These results reflect the fact that the stocks which comprise the Agricultural sector have quite high share prices. This can be attributed to the fact that these stocks are mature, with a considerable accumulation of capital gains, and their shares have never been split. Conversely, the Telecommunications & Technology sector has

the least aggregate index value because it consists of only one stock that has a relatively low - but consistently increasing - share price.

Most series have a positive value for skewness, implying that their distributions are asymmetrical with fat left tails. This is indicative that the weekly closing values of all indexes do not follow a normal distribution (Skewness of a Normal Distribution=0). On kurtosis, it can be seen that all values for this measure are less than that of a normal distribution (Kurtosis of a Normal Distribution=3). Therefore, the distributions of the weekly closing values of all indexes are platykurtic and their levels of peakedness are less than that of a normal distribution. These findings are in line with Athanasopoulos *et al* (2014) who posit that stock indexes follow a non stationary random walk process with a trend, and hence their observations usually do not follow a normal distribution.

It is noteworthy that the values of the indexes depend on the actual market prices of the stocks that are listed under them; and whether such stocks have been subjected to share splits or not. Therefore, these values are not indicative of the relative performances of the various sectors at all.

Table 4.2: Descriptive Statistics of Sectoral Weekly Returns

Sector	Mean	Max	Min	S Dev.	Skewness	Kurtosis
Agricultural	0.001509	0.1601	-0.2373	0.0296	-0.4941	16.9294
Automobiles & Accessories	-0.001266	0.1484	-0.1352	0.0362	0.1520	5.3357
Banking	0.000491	0.1489	-0.1297	0.0255	0.0535	8.2875
Commercial & Services	-0.002214	0.1565	-0.2733	0.0297	-1.0764	16.9893
Construction & Allied	-0.000665	0.1016	-0.0738	0.0231	0.1272	4.4334
Energy & Petroleum	-0.000482	0.1396	-0.1265	0.0337	0.3265	5.1573
Insurance	0.001994	0.2135	-0.1509	0.0356	0.4230	7.5382
Investment	-0.000018	0.2213	-0.1582	0.0451	0.6270	5.5516
Manufacturing & Allied	-0.000195	0.1426	-0.2556	0.0289	-0.8769	15.2730
Telecommunications & Technology	0.002323	0.1749	-0.2603	0.0414	-0.4360	6.7860

Source: Study Data (2019)

As per Table 4.2, the Telecommunications & Technology sector is the best performing sector for the measurement period, with average weekly returns of 0.2323%. This can be attributed to the fact that the Telecommunications & Technology sector is a growth sector which hasn't yet reached its terminal phase (Owidi and Waweru, 2016). Therefore, it is abound with unexploited opportunities. Moreover, this sector is dominated by Safaricom PLC, which has been the most profitable listed firm in East and Central Africa for a considerable duration of time. Naturally, this has led to an impressive bull run in Safaricom PLC's stock. This is in tandem with Ahmed (2016) who notes that on average; newly emergent sectors tend to offer more attractive returns than old, mature sectors.

On the other hand, the Commercial & Services sector is the least performing sector, with a mean average return of -0.2214%. Ostensibly, this poor performance of this sector can be attributed to the erosion of market value which has bedeviled some of its constituent firms (such as Express Kenya, Kenya Airways, and Uchumi) consistently over time. In summary, the Telecommunications & Technology, Insurance, Agricultural, and Banking sectors have positive average weekly returns while the mean weekly returns of the Investment, Manufacturing & Allied, Energy & Petroleum, Construction & Allied, Automobiles & Accessories, and Commercial & Services sectors are negative.

The large deviations between the maximum and minimum observations indicate the existence of sizeable dispersion of returns and prevalence of huge shocks to the 10 sectors' indexes. The standard deviations of the weekly returns imply that the Investment sector is the most volatile (Standard deviation=0.0451) while the Construction & Allied sector is least volatile (Standard deviation=0.0231). On skewness, all returns series have skewed, non normal distributions (Skewness of a Normal Distribution=0): The distributions of the Investment, Insurance, Energy & Petroleum, Automobiles & Accessories, Construction & Allied, and Banking sectors are positively skewed while those of the Telecommunications & Technology, Agricultural, Manufacturing & Allied, and Commercial & Services sectors are negatively skewed.

Furthermore, it can be inferred that all returns series are leptokurtic, since their levels of kurtosis are higher than the kurtosis of a normal distribution (Kurtosis of a Normal Distribution=3). These findings are in line with *a priori* expectations. The literature (Asai and Mcleer, 2011; Engle, 2003; Brooks, 2008; Engle, Ito and Lin, 1990) affirms that financial returns usually do not follow a normal distribution, but rather they exhibit their stylized facts;

key of which are the presence of leptokurtosis, non-zero skewness, and conformance to fat tailed distributions.

Table 4.3: Descriptive Statistics of Sectoral Weekly Liquidity

Sector	Mean	Max	Min	S Dev.	Skewness	Kurtosis
Agricultural	0.00117	0.02004	0.00002	0.00193	4.9	34.7
Automobiles & Accessories	0.00066	0.00626	0.00001	0.00086	3.0	14.5
Banking	0.00176	0.01245	0.00015	0.00124	3.3	23.8
Commercial & Services	0.00050	0.00805	0.00001	0.00059	5.3	55.7
Construction & Allied	0.00107	0.03535	0.00002	0.00208	10.0	144.4
Energy & Petroleum	0.00123	0.01899	0.00001	0.00167	4.4	34.9
Insurance	0.00165	0.03993	0.00004	0.00235	8.7	130.0
Investment	0.00607	0.13889	0.00009	0.01291	5.5	43.5
Manufacturing & Allied	0.00234	0.03006	0.00016	0.00208	5.7	63.8
Telecommunications & Technology	0.00145	0.01143	0.00009	0.00107	3.2	22.6

Source: Study Data (2019)

It can be inferred from Table 4.3 that the Investment sector has the highest level of mean weekly liquidity (0.0060). Moreover, the Manufacturing & Allied and Banking sectors have the second and third highest levels of average weekly liquidity respectively. On the other hand, the Commercial & Services sector has the least level of mean weekly liquidity (0.0005). The Investment sector also has the highest level of liquidity on record for the data collection period (max=0.13889) while the Automobiles & Accessories sector has the least level of liquidity on record for the study period (min=0.00001).

Moreover, the liquidity of the Investment sector exhibits the highest level of dispersion (standard deviation=0.01291) while the Commercial & Services sector has the least level of variability (standard deviation=0.00059). It is apparent that the liquidity series of all 10 sectors are heavily skewed to the right. This can be inferred from the fact that all coefficients of skewness are greater than 0. Furthermore, the liquidity of the NSE's sectors has extremely high levels of kurtosis, as compared to the kurtosis of a normal distribution, thereby implying that they follow leptokurtic distributions.

4.3 Trend Analysis of the Sectoral Indexes, Returns and Liquidity

The study conducted a trend analysis on the weekly closing values, weekly returns, and weekly liquidity of the 10 sectoral indexes. Each time plot illustrates the temporal variability of its respective series over 13th June 2008 to 8th February 2019 period. Figure 4.1 depicts the general trend in the weekly closing values of the 10 sectors' indexes, while Figure 4.2 shows the trend of the sectors' weekly returns. Further, Figure 4.3 illustrates the trend in the weekly liquidity of the 10 sectors.

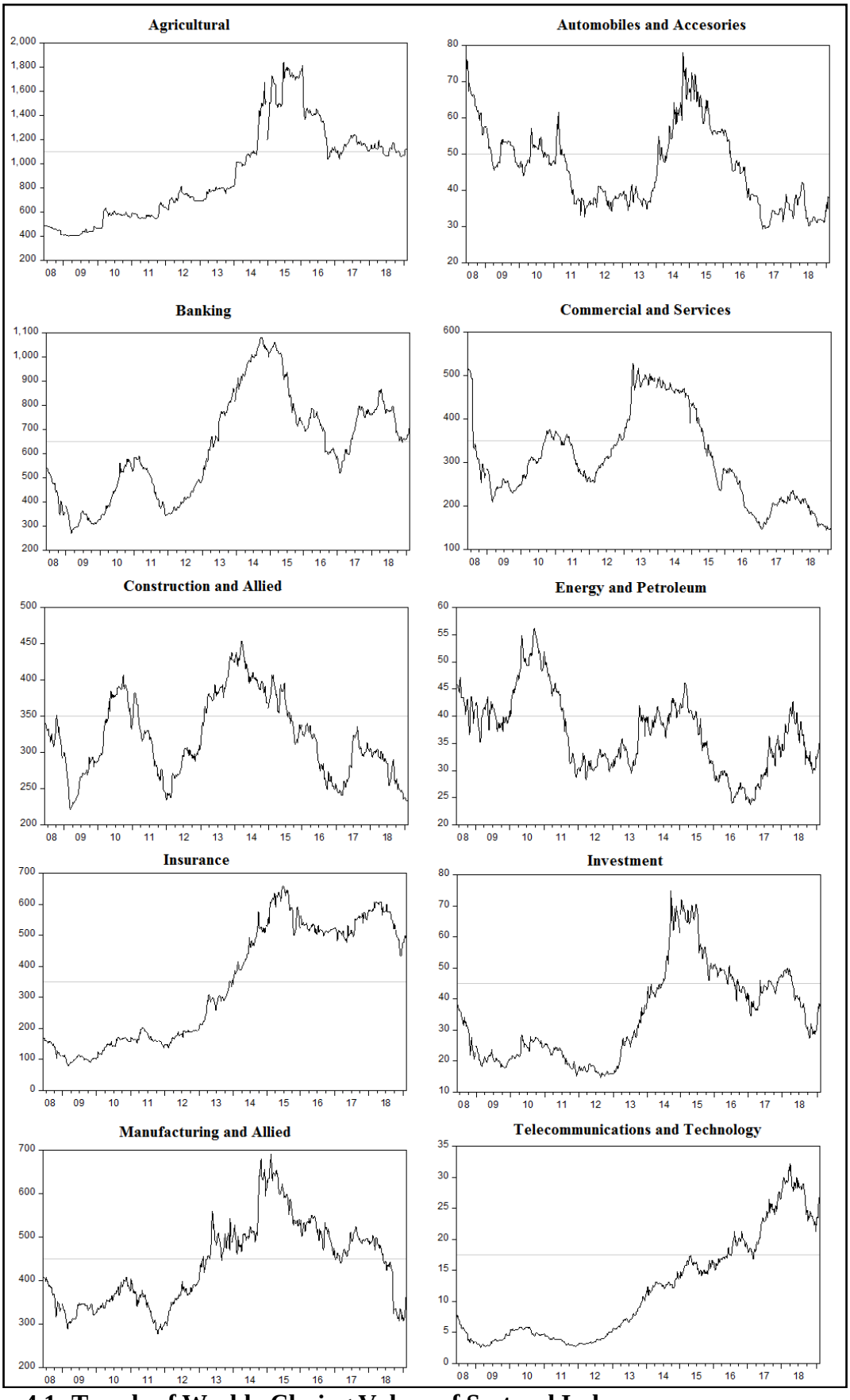

Figure 4.1: Trends of Weekly Closing Values of Sectoral Indexes

It can be inferred from Figure 4.1 that there is a systematic decline in all indexes as from the second quarter of 2008. Ostensibly, this can be attributed to the fact that as at the start of the data collection period, the NSE's equities were still reeling from the bear run of 2008 that was brought about by the global financial crisis and Kenyan post election strife of 2007/2008. Nevertheless, there is a general upward trend in all indexes as from the second quarter of 2009 until the end of the second quarter of 2010 when all indexes appear to go on a downward trend again.

For majority of the indexes, the most prominent Bull Run commences around the start of 2012 and peaks in the second quarter of 2014. After this period, most sectors enter in a period of extreme decline as from the first quarter of 2015 but recover marginally in a small rebound in the third quarter of 2017. However, other sectors (such as Telecommunications & Technology, Agricultural, and Banking) do not suffer this decline to a big extent and they largely manage to hold on to their value. It can be noticed that the indexes of these sectors follow a random walk process with an upward trend process over the better part of the measurement period. This implies that they are robust to the macroeconomic and idiosyncratic factors that could have led to tremendous shifts in the market values of other sectors' indexes. This robustness is affirmed by the fact that these three sectors have the highest mean weekly returns.

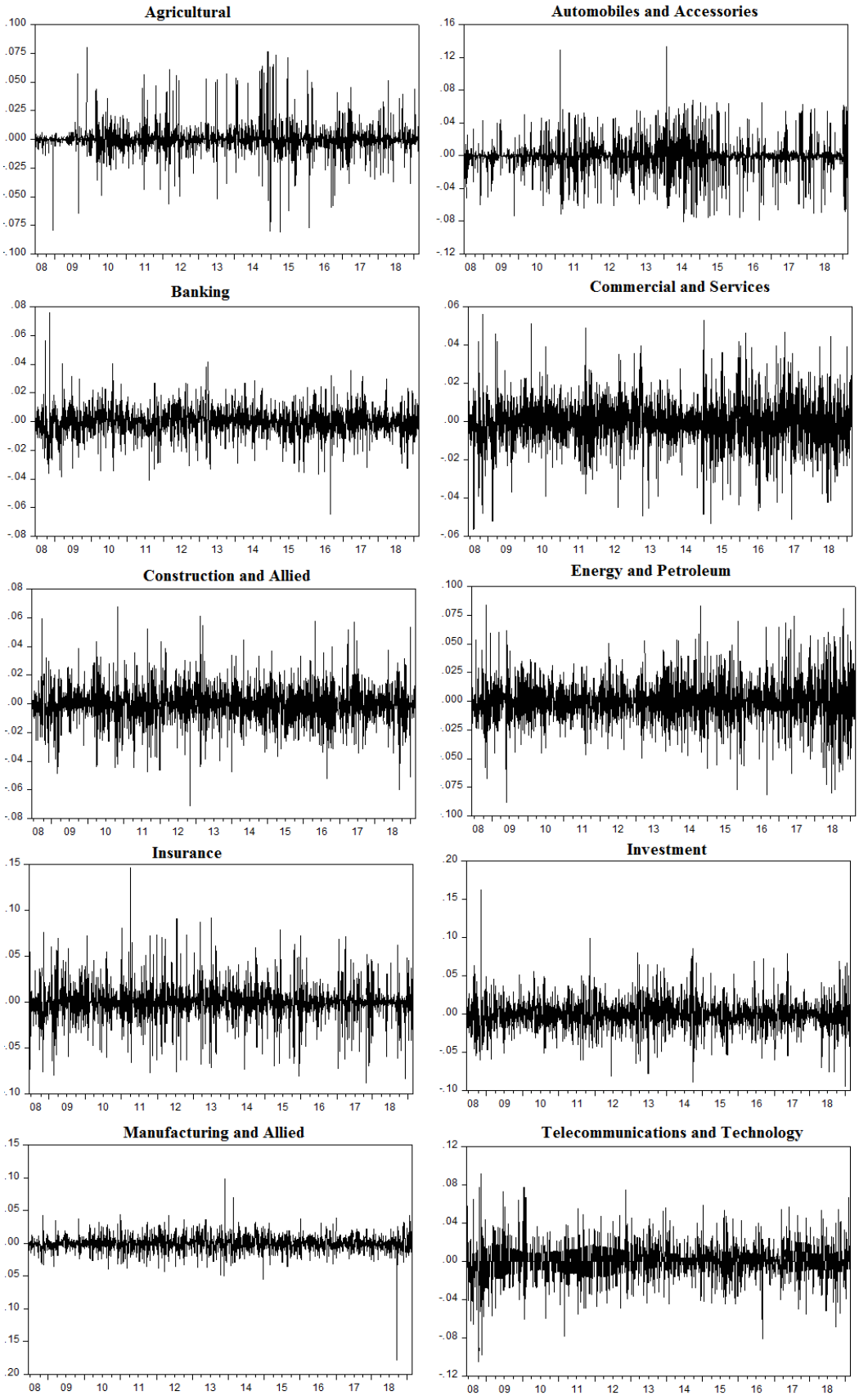

Figure 4.2: Trends of Weekly Returns of Sectoral Indexes

Figure 4.2 depicts time plots of the NSE sectors' weekly returns. Visually, it is inferable that the sectoral returns are stationary; since they are all mean reverting to a mean of zero. Additionally, it is plainly visible that the variability of the returns is time varying - an indicator of the presence of conditional heteroscedasticity. The time plots further show that the sectoral returns exhibit volatility clustering. According to Engle (1982), this phenomenon of financial time series is characterized by the tendency of periods of large returns to follow each other consequentially. Likewise, periods of small returns also tend to be followed by periods of small returns. It can be noticed that the volatility clusters form mostly in periods when the respective index is either in a general trend of appreciation or decline. Nevertheless, security prices follow a pure random walk process and it's not possible to predict when the index of any sector will start declining or appreciating purely on the basis of historical information (Brooks, 2008). According to Ruiz (2014), such behavior of asset prices accentuates investor uncertainty thereby leading to higher levels of volatility in periods of rapid price changes than in periods of relative stability.

Figure 4.2 also shows that some sectors (such Agricultural and Automobiles & Accessories) have thinly traded stocks. This is inferable from the observation that time plots of these sectors are less dense, ostensibly due to the fact that their numbers of unique returns over the data collection period are quite low. On the other hand, some plots are quite dense (such as Telecommunications & Technology), due to an apparently high multiplicity of unique returns and a large turnover of stocks. The presence of extreme negative shocks (such as in the Manufacturing & Allied sector) and extreme positive shocks (the Investment and Insurance sectors) can also be noticed. From Figure 4.2, the phenomenon of leptokurtosis is also visible. In all plots, the returns are heavily concentrated at or near the mean of zero, than would be in case the returns followed a normal distribution.

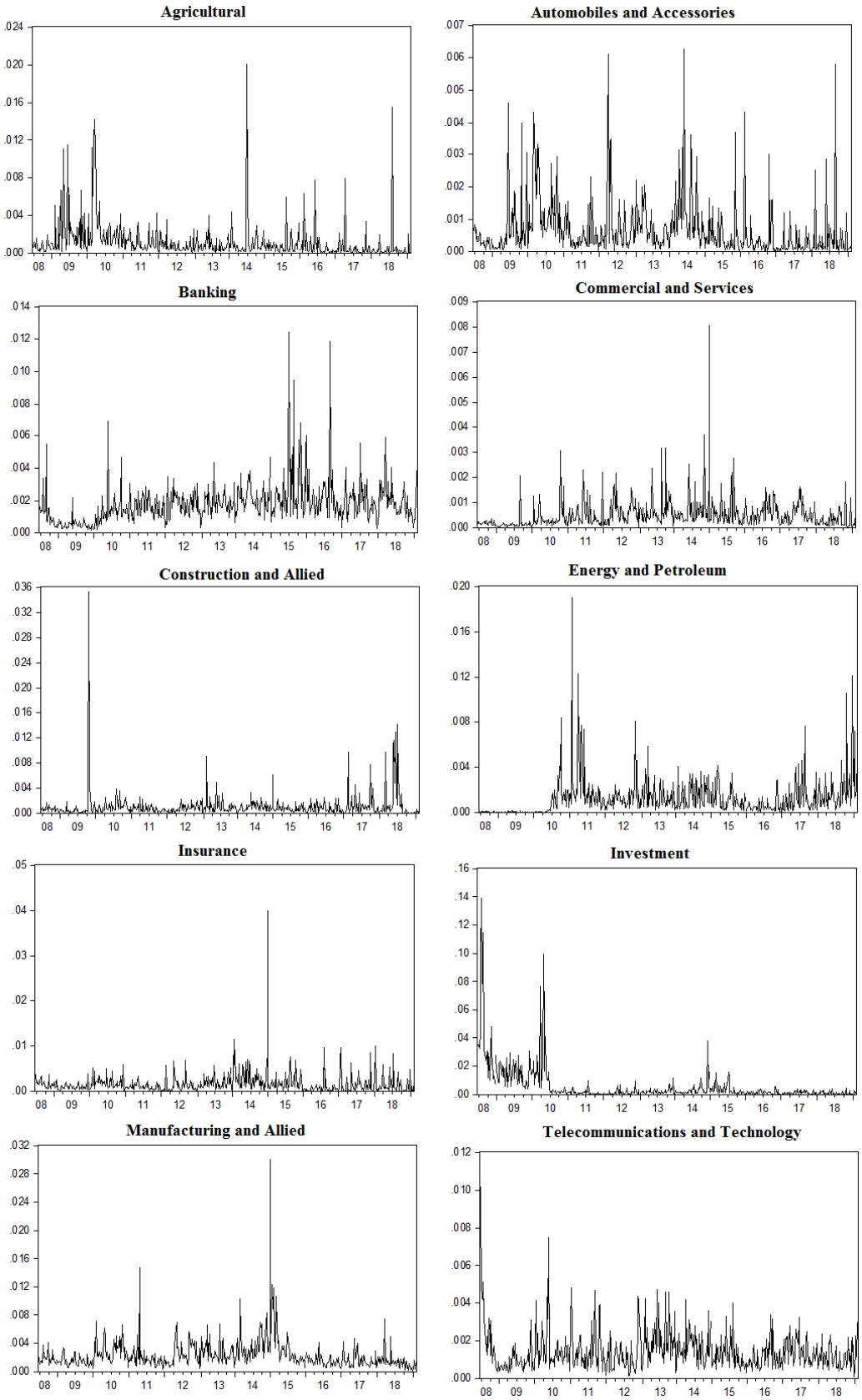

Figure 4.3: Trends of Weekly Sectoral Liquidity

It can be seen From Figure 4.3 that all sectors of the NSE have periods in which there is extreme investor demand, leading to huge spikes in stock turnover, and hence liquidity. The periods of liquidity surge are unique to each sector. However, it can be noticed that between the second quarter of 2014 and first quarter of 2015, there is a systematic increment in investor demand in the entire market. From Figure 4.1, it is noticeable that this is the exact period when the index values of all sectors were soaring. Unsurprisingly, there is also an elevation in volatility during this time, as evident in Figure 4.2. Finally, it can be noticed that some sectors have more surges in stock turnover, as compared to others.

4.4 Diagnostic Testing

In a bid to ensure aptness of the data to analysis using the GARCH approach, diagnostic testing was undertaken. Diagnostic testing is key since it augments model selection and specification processes. There are three main pre-estimation requirements that must be met before fitting GARCH models: First, all raw returns series must be stationary. Second, in the case of Multivariate GARCH analysis, the mean equation should be fitted using the appropriate model: A VEC specification should be utilized for the mean equation in case there are cointegration relations and non stationarity in the raw data while a VAR mean equation model is appropriate if the variables are stationary at levels. Finally, ARCH effects must be present in the raw data. This phenomenon is deemed present in a multivariate setting when the cross products of residuals are autocorrelated and their covariance matrix is not fixed but time-varying. On the other hand, univariate GARCH effects are present if the residuals of the univariate mean equation are autocorrelated (Bauwens, Laurent and Rombouts, 2006).

4.4.1 Testing for Stationarity

The study utilized Augmented Dickey Fuller (ADF) tests to test the weekly returns series for stationarity. This test is based on the null hypothesis that a given time series has a unit root, against the alternative hypothesis that the series is stationary. The null hypothesis of a unit root should be rejected at any given level of significance if the ADF test statistic is less that the respective critical value for the specified level of significance (Fuller, 1976). Table 4.4 shows the results of the ADF Tests for the 10 NSE sectors' returns series.

Table 4.4: ADF Tests for Returns Series

Returns Series	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Agricultural	-21.072	-3.43	-2.86	-2.57
Automobiles & Accessories	-24.524	-3.43	-2.86	-2.57
Banking	-19.864	-3.43	-2.86	-2.57
Commercial & Services	-20.111	-3.43	-2.86	-2.57
Construction & Allied	-21.610	-3.43	-2.86	-2.57
Energy & Petroleum	-24.332	-3.43	-2.86	-2.57
Insurance	-26.121	-3.43	-2.86	-2.57
Investment	-24.502	-3.43	-2.86	-2.57
Manufacturing & Allied	-24.037	-3.43	-2.86	-2.57
Telecommunications & Technology	-25.804	-3.43	-2.86	-2.57

Source: Study Data (2019)

As per the results of the ADF tests in Table 4.4, all ADF test statistics are less than their corresponding critical values at all levels of significance. Therefore, the null hypothesis of a unit root is rejected for all returns series at the 1% level of significance and the conclusion is that all returns series are stationary at levels. In order to enhance the robustness of the research and to be absolutely sure of stationarity in the raw data, the study triangulated the results of the ADF test using Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for stationarity. In contrast to ADF tests, KPSS tests are based on the null hypothesis that a time series is stationary against the alternative that the time series has a unit root. At any given level of significance, the null hypothesis of stationarity should be rejected if the KPSS test statistic is larger than the respective critical value for the specified level of significance. Table 4.5 shows the results of KPSS tests for the NSE sectors' returns series.

Table 4.5: KPSS Tests for Returns Series

Returns Series	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Agricultural	0.1150	0.216	0.146	0.119
Automobiles & Accessories	0.0872	0.216	0.146	0.119
Banking	0.0921	0.216	0.146	0.119
Commercial & Services	0.0775	0.216	0.146	0.119
Construction & Allied	0.0756	0.216	0.146	0.119
Energy & Petroleum	0.0549	0.216	0.146	0.119
Insurance	0.1160	0.216	0.146	0.119
Investment	0.1090	0.216	0.146	0.119
Manufacturing & Allied	0.0942	0.216	0.146	0.119
Telecommunications & Technology	0.1050	0.216	0.146	0.119

Source: Study Data (2019)

As per Table 4.5, the KPSS test statistics of all 10 returns series are less than their critical values at all levels of significance. Therefore, the null hypothesis of stationarity is not rejected for all series at the 1% level of significance, implying that the 10 returns series are stationary at levels. After affirming that the sectoral returns series were stationary at levels, the study didn't deem it necessary to undertake cointegration tests to since cointegration, by definition, does not exist in stationary data. Consequently, the multivariate mean equation for this study was estimated as a VAR model.

4.4.2 Testing for Multivariate ARCH Effects

In order to fit any ARCH - type model, whether univariate or multivariate, ARCH effects must be present (Engle, 1982). If ARCH effects are present in a time series variable, the squared residuals of this variable's mean equation will be autocorrelated. Such autocorrelation makes it possible to model a time series variable's conditional heteroscedasticity as a function of past shocks (Engle, 1982; Bollerslev, 1986, Brooks, 2008). Multivariate ARCH effects are present if the cross products of residuals from the estimation of the mean equation are autocorrelated and their variance-covariance matrix is dynamic. In order to evaluate the presence of multivariate ARCH effects, the study used the Hacker and Hatemi-J LM test. This test is based on the null hypothesis that the cross products of residuals are not autocorrelated and their covariance matrix is fixed; against the null hypothesis that the cross products of residuals are autocorrelated and their covariance matrix is time-varying (Hacker and Hatemi-J, 2005). The results of the Hacker and Hatemi-J (2005) LM test for Multivariate ARCH LM effects are shown in Table 4.6.

Table 4.6: Hacker & Hatemi-J LM Test for Multivariate ARCH effects

Test Statistic	Degrees of Freedom	Signif
12713.99	3025	0.0000

Source: Study Data (2019)

As evident in Table 4.6, the test for Multivariate ARCH effects is statistically significant at the 1% level. Therefore, the null hypothesis that the cross products of residuals are not serially correlated and that they have a fixed covariance matrix is rejected in favor of the alternative that the cross products of residuals are serially correlated and that their covariance matrix is dynamic. In other words, multivariate ARCH effects are deemed to be present.

4.5 Empirical Model Fitting

Diagnostic testing ascertained that the returns series were stationary at levels and multivariate ARCH effects were present. Hence, the data was deemed apt for analysis using GARCH models. Data analysis was undertaken in two phases: The first phase was to fit the VAR-BEKK-MGARCH model, whose results were necessary to test the first four hypotheses of the study. Estimating the VAR-BEKK-MGARCH model entailed fitting a VAR(1) mean equation and a VAR(1) BEKK-MGARCH(1,1) variance equation. After discussing the results of testing its first four hypotheses, the study undertook the second phase of data analysis, which entailed utilization of univariate GARCH models to test its fifth hypothesis.

4.5.1 Fitting the VAR Mean Equation

Since the returns series were stationary at levels, a VAR model was used to fit the mean equation. Prior to estimation of the mean equation, the study undertook an optimal lag order selection procedure.

4.5.1.1 Optimal Lag Order Selection

Brooks (2008) notes that selection of the optimal number of lags is essential since it helps in ensuring that the multivariate mean equation gets fitted using the number of lags that is appropriate for the underlying data structure. Following Wanja (2017), the study utilized the four most common information criteria to establish the optimal lag order. These criteria are the: Final prediction error (FPE), Akaike information Criterion (AIC), Schwarz Bayesian information criterion (SBIC) and Hanna Quinn Information criterion (HQIC). The results of optimal lag order selection are depicted in Table 4.7.

Table 4.7: Lag length selection criteria

Lag	LogL	LR	FPE	AIC	SBIC	HQIC
0	11371.620	NA	3.17E-31	-41.848	-41.76843*	-41.817*
1	11487.100	226.295*	2.99E-31*	-41.905*	-41.034	-41.564
2	11549.220	119.430	3.44E-31	-41.765	-40.103	-41.115
3	11607.140	109.219	4.03E-31	-41.610	-39.157	-40.651
4	11678.840	132.574	4.47E-31	-41.506	-38.261	-40.237
5	11724.570	82.877	5.48E-31	-41.306	-37.270	-39.728
6	11794.210	123.629	6.15E-31	-41.194	-36.367	-39.307
7	11856.620	108.507	7.10E-31	-41.056	-35.437	-38.859
8	11915.130	99.555	8.34E-31	-40.903	-34.493	-38.397
9	11975.530	100.568	9.74E-31	-40.757	-33.556	-37.941
10	12053.490	126.914	1.07E-30	-40.676	-32.683	-37.551

Source: Study Data (2019)

As manifest in Table 4.7, most criteria indicated that the optimal lag order for fitting the mean model was one. Therefore, the VAR mean equation was fitted using one lag, i.e. as a VAR (1) model.

4.5.1.2 VAR (1) Mean Equation Results

The results of fitting the VAR (1) mean equation are depicted in Table 4.8; which shows the respective estimated coefficients together with their t statistics and p values. This is the output for Equation 3.3; Section 3.4.2. The elements of equation 3.3's vector α are the intercept coefficients that are shown in Table 4.8, while elements of equation 3.3's matrix θ' are represented by the 100 coefficients of independent variables that are also depicted in Table 4.8. They measure the own and cross influences of sectoral returns in any given week from the returns of the previous week.

Table 4.8: VAR(1) Mean Equation Results

		Dependent Variables									
		$R_{1,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{5,t}$	$R_{6,t}$	$R_{7,t}$	$R_{8,t}$	$R_{9,t}$	$R_{10,t}$
		j=1	**j=2**	**j=3**	**j=4**	**j=5**	**j=6**	**j=7**	**j=8**	**j=9**	**j=10**
	Intercepts										
	α_j	0.001	0.003*	0.000	0.02**	-0.001	0.000	0.002	-0.001	0.000	0.002
	T-Stat	0.633	1.918	0.321	1.967	-0.908	-0.207	1.309	-0.442	-0.422	1.396
	P Value	0.527	0.055	0.749	0.049	0.364	0.836	0.19	0.658	0.673	0.163
Independent Variables	**Coefficients**										
$R_{1,t-1}$	θ_{1j}	*0.11***	0.047	0.024	0.002	0.031	-0.071	0.021	0.042	-0.05	-0.061
	T-Stat	*2.685*	0.969	0.801	0.047	1.07	-1.602	0.421	0.742	-1.463	-1.161
	P Value	*0.007*	0.333	0.423	0.963	0.285	0.109	0.674	0.458	0.143	0.246
$R_{2,t-1}$	θ_{2j}	0.002	*0.074**	0.015	0.016	0.034	0.021	0.049	0.044	0.016	0.018
	T-Stat	0.067	*1.914*	0.616	0.546	1.395	0.602	1.306	0.976	0.546	0.411
	P Value	0.947	*0.056*	0.538	0.585	0.163	0.547	0.192	0.329	0.585	0.681
$R_{3,t-1}$	θ_{3j}	0.028	0.15***	*0.066*	0.19***	0.09**	0.11**	0.32***	0.138*	0.058	0.066
	T-Stat	0.595	2.643	*1.335*	3.643	2.299	2.035	4.732	1.724	1.123	0.929
	P Value	0.552	0.008	*0.182*	0.000	0.022	0.042	0.000	0.085	0.261	0.353
$R_{4,t-1}$	θ_{4j}	0.025	-0.022	0.058	*-0.024*	0.01	0.05	-0.02	0.058	0.035	-0.046
	T-Stat	0.71	-0.401	1.588	*-0.515*	0.358	1.183	-0.419	0.939	0.917	-0.75
	P Value	0.478	0.689	0.112	*0.607*	0.72	0.237	0.675	0.348	0.359	0.453
$R_{5,t-1}$	θ_{5j}	0.02	0.103*	0.052	0.11**	*0.009*	0.093*	0.018	-0.037	0.058	-0.045
	T-Stat	0.392	1.679	1.211	2.241	*0.246*	1.703	0.311	-0.497	1.291	-0.619
	P Value	0.695	0.093	0.226	0.025	*0.805*	0.089	0.756	0.619	0.197	0.536
$R_{6,t-1}$	θ_{6j}	-0.012	0.029	0.021	-0.003	0.011	*0.17***	0.032	0.056	0.04	-0.008
	T-Stat	-0.303	0.658	0.699	-0.081	0.446	*2.548*	0.81	1.115	1.357	-0.166
	P Value	0.762	0.511	0.484	0.935	0.655	*0.011*	0.418	0.265	0.175	0.868
$R_{7,t-1}$	θ_{7j}	-0.001	0.019	-0.012	0.002	0.035	-0.057	*0.25****	-0.029	0.001	0.038
	T-Stat	-0.017	0.496	-0.439	0.066	1.541	-1.603	*6.906*	-0.569	0.001	0.885
	P Value	0.987	0.62	0.66	0.947	0.123	0.109	*0.000*	0.569	0.999	0.376
$R_{8,t-1}$	θ_{8j}	0.042*	0.003	0.07***	0.036	0.016	0.013	0.12***	*0.14****	0.034	0.055
	T-Stat	1.743	0.101	3.406	1.405	0.86	0.501	4.151	*3.407*	1.493	1.463
	P Value	0.081	0.922	0.001	0.161	0.39	0.616	0.000	*0.001*	0.135	0.143
$R_{9,t-1}$	θ_{9j}	0.039	-0.012	0.004	0.021	0.037	0.18***	0.005	0.078	*0.069**	0.028
	T-Stat	1.063	-0.243	0.114	0.591	1.229	3.891	0.116	1.321	*1.688*	0.464
	P Value	0.288	0.808	0.909	0.554	0.219	0.000	0.907	0.186	*0.091*	0.643
$R_{10,t-1}$	θ_{10j}	0.044	0.075*	0.058*	0.019	0.007	0.034	0.025	0.09**	0.031	*0.11****
	T-Stat	1.461	2.182	2.483	0.625	0.329	1.157	0.833	2.425	1.152	*2.864*
	P Value	0.144	0.029	0.013	0.532	0.743	0.247	0.405	0.015	0.251	*0.004*

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)

It can be inferred from Table 4.8 that the intercept coefficients of the returns models for the Automobiles & Accessories and Commercial & Services sectors are statistically significant at the 10% and 5% levels respectively. This implies that the returns of each of these two sectors follow an autoregressive process with a drift (Taly, 2015).

The diagonal coefficients of Table 4.8 represent the own return spillover effects. This is tendency of returns that are realized in any given week to influence the following week's returns (Hung, 2019). For all sectors except three (Banking, Commercial & Services, and Construction & Allied), it can be noticed that there exists positive own transmission effects of returns. This implies that in each of these seven sectors, the returns for any given week are influenced positively by their own value from the preceding week.

The off diagonal coefficients of Table 4.8 measure the cross-sector return spillover effects. This effect arises from the tendency of sectoral returns in one period to spillover, thereby influencing next period returns of other sectors, due to sectoral interrelatedness (Lee, Naranio, and Simans, 2014). From this table, there is evidence of positive unidirectional cross spillover effects of returns from the Investment sector to the Agricultural sector. Moreover, unidirectional cross spillovers of returns from the Banking, Construction & Allied, and Telecommunications & Technology sectors to the Automobiles & Accessories sector are also detected. Returns of the banking sector are influenced unidirectionally by those of the Telecommunications & Technology sector; and, there is bidirectional spillover of returns between the Investment and Banking Sectors. Moreover, there is evidence of unidirectional cross spillover of returns from the Construction & Allied Sector to the Commercial & Services Sector; and returns of the Construction & Allied Sector are found to be influenced only by lagged returns of the Banking sector. Additionally, cross spillovers of returns from

the Manufacturing & Allied, Construction & Allied, and Banking sectors to the Energy & Petroleum sector are detected. Returns of the Insurance sector are found to be affected by spillovers of returns from the Investment and Banking sectors. Furthermore, cross returns spillovers from Telecommunications & Technology and Banking Sectors to the Investment Sector are noticed. For the Manufacturing & Allied and Telecommunications & Technology Sectors, no cross spillovers of returns are evident.

Past returns of the Banking sector have an influence on the highest number of NSE sectors: It can be noticed that they affect the returns of six other sectors. This can be attributed to the fact that the Banking sector is interrelated with all other sectors due to the fact that it plays the key role of financing their operations and assets.

4.5.2 Fitting the VAR (1) BEKK-MGARCH (1,1) Variance Equation

After estimation of the VAR (1) mean equation, the BEKK-MGARCH multivariate variance equation was fitted. The literature (Mohammadi and Tan, 2015; Mootamri, 2011; Bauwens *et al*, 2006) holds that fitting multivariate GARCH models with a single lag for both ARCH terms and GARCH terms yields the most parsimonious estimation of such models. Therefore, the BEKK-MGARCH variance model was fitted using the BEKK-MGARCH(1,1) specification. This entailed estimation of the coefficients of matrices *C, A* and *B* as described in section 3.4.3, by fitting equation 3.9. A major part of this section is dedicated to discussion of the results of estimating matrices *C, A,* and *B.* Moreover, the results of testing the first four hypotheses of this study are also presented, since the coefficients of matrices *A* and *B* form the basis of testing these hypotheses.

Matrix *C* contains intercept coefficients for the volatility and covolatility processes of the NSE's 10 sectors, while Matrix *A*'s coefficients measure how volatility in the NSE's sectors in any given week is influenced by own and cross sectoral shocks from the preceding week. Matrix *B*'s coefficients quantify how volatility in the NSE's 10 sectors in any given week is affected by the persistence of own and cross sectoral volatilities from the previous week.

4.5.2.1 Intercept Coefficients - Matrix C

The intercept coefficients of time series models represent their long term drift. Bernhardt (2017) notes that the drift of volatility and covolatility processes is a constant term by which the observed value of a process at any given time is adjusted with when estimating the next period's observation. The drift coefficients for this study's volatility and covolatility processes are depicted in Table 4.9.

Table 4.9: Intercept Coefficients - Matrix C

	Dependent Variables									
	$\sigma^2_{1,t}$ **j=1**	$\sigma^2_{2,t}$ **j=2**	$\sigma^2_{3,t}$ **j=3**	$\sigma^2_{4,t}$ **j=4**	$\sigma^2_{5,t}$ **j=5**	$\sigma^2_{6,t}$ **j=6**	$\sigma^2_{7,t}$ **j=7**	$\sigma^2_{8,t}$ **j=8**	$\sigma^2_{9,t}$ **j=9**	$\sigma^2_{10,t}$ **j=10**
Drift Constants										
C_{1j}	0.014***	0.01**	0.007*	-0.001	0.01**	0.014*	0.003	0.002	0.003	0.002
T-Stat	6.056	2.502	1.680	-0.288	2.087	1.880	1.277	0.861	0.536	0.712
P Value	0.000	0.012	0.093	0.773	0.037	0.060	0.202	0.389	0.592	0.476
C_{2j}		0.03***	0.004	0.005*	0.003	0.006	0.001	0.002	0.09***	0.001
T-Stat		6.542	1.447	1.723	0.954	1.283	0.799	1.076	2.272	0.557
P Value		0.000	0.148	0.085	0.340	0.199	0.424	0.282	0.023	0.577
C_{3j}			0.021***	0.01***	0.004*	0.006	0.11***	0.02***	0.01***	0.015***
T-Stat			16.313	6.169	1.785	1.491	3.741	3.940	3.437	4.713
P Value			0.000	0.000	0.074	0.136	0.000	0.000	0.001	0.000
C_{4j}				0.06***	0.002	0.007**	0.004**	0.002	0.003	0.005**
T-Stat				18.407	1.196	2.347	2.336	0.970	1.346	2.230
P Value				0.000	0.232	0.019	0.019	0.332	0.178	0.026
C_{5j}					0.052***	-0.005	0.087	0.005	0.014	0.085
T-Stat					4.938	-0.789	0.137	1.324	0.047	0.062
P Value					0.000	0.430	0.891	0.185	0.963	0.950
C_{6j}						0.029***	0.002	0.010	-0.002	0.010**
T-Stat						3.323	0.667	1.512	-0.524	2.128
P Value						0.001	0.505	0.131	0.600	0.033
C_{7j}							0.071***	-0.002	0.005	-0.005
T-Stat							2.861	-0.361	1.425	-0.932
P Value							0.004	0.718	0.154	0.351
C_{8j}								0.058***	0.004	-0.007
T-Stat								2.880	0.736	-0.924
P Value								0.004	0.462	0.355
C_{9j}									0.024***	0.018**
T-Stat									4.141	2.016
P Value									0.000	0.044
C_{10j}										0.001
T-Stat										0.001
P Value										0.999

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)

Except for the Telecommunications & Technology sector, it can be noticed from Table 4.9 that the long term drift coefficients of the other 9 sectors' volatilities are statistically significant at the 1% level. This implies that the volatility of each of these 9 sectors has a constant drift adjustment for each week which shifts their volatility processes from the unconditional mean of zero. In the absence of the effect of independent variables (past shocks and volatilities) it would take a considerably long duration of time for the volatility processes of these sectors to mean-revert (Lütkepohl, 2005). This can be attributed to the fact that GARCH processes have long memory and shocks are assumed to influence volatility almost infinitely into the future (McCauley, 2009). Jorion (2007) concurs and adds that in processes that have drift, it can take a very long time for volatility to die off in the absence of new shocks; especially if they also have a high persistence of volatility. However, for the Telecommunications & Technology sector, there is no such steady drift adjustment and the absence of new shocks in this sector would result in a quicker rate of mean reversion to zero.

Moreover, it is evident in Table 4.9 that the drift coefficients of 17 covolatility processes were statistically significant. This implies that due to drifting, these 17 processes would take a longer time before complete mean reversion in absence of the influence of lagged cross products of residuals and lagged covariances of residuals, as compared to zero drift covolatility processes (Bernhardt, 2017). The pairs of sectors with significant covolatility drift coefficients are: (Agricultural, Automobiles & Accessories), (Agricultural, Banking), (Agricultural, Construction & Allied), (Agricultural, Energy & Petroleum), (Automobiles & Accessories, Commercial & Services), (Automobiles & Accessories, Manufacturing & Allied), (Banking, Commercial & Services), (Banking, Construction & Allied), (Banking, Insurance), (Banking, Investment), (Banking, Manufacturing & Allied), (Banking, Telecommunications & Technology), (Commercial & Services, Energy & Petroleum),

(Commercial & Services, Insurance), (Commercial & Services, Telecommunications & Technology), (Energy & Petroleum, Telecommunications & Technology) and (Manufacturing & Allied, Telecommunications & Technology).

4.6 Hypothesis Testing

The coefficients contained in Matrices *A* and *B* provided the basis for testing the first four hypotheses of this research. Hypotheses *i* and *ii* focused on the relationship between past shocks and volatility in the 10 sectors of the NSE, while hypotheses *iii* and *iv* were on the relationship between past volatility and (current) volatility in the NSE's sectors. After testing the first four hypotheses of the study, hypothesis *v* was then tested separately via the utilization of univariate GARCH (1,1) models and univariate GARCH (1,1) models with exogenous variance regressors.

4.6.1 Relationship between Past Shocks and Volatility of Returns

Matrix A's coefficients enabled the study to make inferences on whether the level of volatility of each NSE sector, in any given week, is affected by shocks that impacted its own returns and the returns of other NSE sectors in the previous week. For the sake of clarity, the coefficients of matrix *A* were populated in two tables after model estimation. The diagonal coefficients of this matrix are shown in Table 4.10 while its off diagonal coefficients are depicted in Table 4.11.

4.6.1.1 Relationship between Own Past Shocks and Volatility of Returns

The first objective of the study was to investigate the influence of own past shocks on volatility of each sector of the NSE. The study intended to find out whether the shocks that impacted each sector in a given week had an influence on its own volatility in the succeeding

week. To attain this objective, the first hypothesis of the study, which is replicated below, was tested.

Hypothesis i

H_{01}: There is no effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{a1}: There is an effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

Table 4.10, which illustrates the estimated diagonal coefficients of matrix ***A*** together with their t statistics and p values, was the basis for testing *Hypothesis i.*

Table 4.10: Diagonal Coefficients of Matrix A

		Dependent Variables									
		$\sigma^2_{1,t}$	$\sigma^2_{2,t}$	$\sigma^2_{3,t}$	$\sigma^2_{4,t}$	$\sigma^2_{5,t}$	$\sigma^2_{6,t}$	$\sigma^2_{7,t}$	$\sigma^2_{8,t}$	$\sigma^2_{9,t}$	$\sigma^2_{10,t}$
Independent Variables	**Coefficients**										
$\varepsilon^2_{1,t-1}$	a_{11}	0.182***									
	T-Stat	7.348									
	P Value	0.000									
$\varepsilon^2_{2,t-1}$	a_{22}		0.364***								
	T-Stat		6.374								
	P Value		0.000								
$\varepsilon^2_{3,t-1}$	a_{33}			0.297***							
	T-Stat			7.384							
	P Value			0.000							
$\varepsilon^2_{4,t-1}$	a_{44}				0.247***						
	T-Stat				4.837						
	P Value				0.000						
$\varepsilon^2_{5,t-1}$	a_{55}					0.152***					
	T-Stat					2.518					
	P Value					0.01					
$\varepsilon^2_{6,t-1}$	a_{66}						0.340***				
	T-Stat						6.559				
	P Value						0.000				
$\varepsilon^2_{7,t-1}$	a_{77}							0.123***			
	T-Stat							5.262			
	P Value							0.000			
$\varepsilon^2_{8,t-1}$	a_{88}								0.226***		
	T-Stat								3.956		
	P Value								0.001		
$\varepsilon^2_{9,t-1}$	a_{99}									0.351***	
	T-Stat									6.728	
	P Value									0.000	
$\varepsilon^2_{10,t-1}$	a_{1010}										0.101***
	T-Stat										4.831
	P Value										0.000

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***) and (**) denotes significance at the 1% and 5% level respectively

Source: Study Data (2019)

It can be seen in Table 4.10 that all diagonal coefficients of matrix ***A*** are statistically significant at the 1% level. Moreover, all coefficients are positive, implying that shocks to each sector in any given week lead to an increment in their own sectoral volatilities in the succeeding week (Bernhardt, 2017). Owing to the magnitude of the coefficients, own shock transmission effects are strongest in the Automobiles & Accessories sector ($a_{22} = 0.364$). On the other hand, the Telecommunications & Technology sector has the weakest own shock transmission effects ($a_{1010} = 0.101$).

These results are in concurrence with Kalu and Ali (2015) who note that past own shocks are significant drivers of sectoral volatility in the Nigerian Stock Exchange. Likewise, Chuchu (2015) finds sectoral own shocks to have a significant influence on the volatility of sampled NSE sectors. Antonakakis (2008) posits that sectors of stock markets in emerging economies are more susceptible to shock-driven changes in volatility as compared to developed nations. This problem mainly arises due to economic challenges that are unique to these countries and the fact that their markets are not robust enough to withstand the effects of own sectoral shocks. Beirne *et al* (2013) concur and add that emerging economies have weak regulation regimes, inadequate market protection measures, and general lack of stock market sturdiness. These drawbacks give leeway to prevalence of hefty responses to own shocks in these markets. The findings are also in tandem with Hammoudeh, Yuan and McAleer (2009) who find significant short run shock transmission effects in the four countries of the Gulf Cooperation Council (GCC) - Kuwait, Qatar, Saudi Arabia and UAE. On the other hand, the study disagrees with Hassan and Malik (2007) who found own shock transmission effects to be insignificant in most of the sampled sectors of the NYSE. In this market, sectoral volatility was found to be more driven by its own persistence *vis a vis* own shocks. Dovi and Jondeau

(2000) also dissent with the results but add that unlike developing markets, volatility in developed markets - like the NYSE and LSE - is more likely to be driven by contagion flows than own shocks, since such markets are relatively more robust in withstanding the effects of shocks. The factors that enhance their robustness include high levels of market efficiency, strong regulatory frameworks, and smooth market operations.

Table 4.11 summarizes the results of testing hypothesis *i*.

Table 4.11: Summary of Results of Testing Hypothesis *i*

Sector	Null Hypothesis	Decision
1	There is no effect of own past shocks on volatility of returns in sector 1 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
2	There is no effect of own past shocks on volatility of returns in sector 2 of the Nairobi Securities Exchange	**Reject H_0**
3	There is no effect of own past shocks on volatility of returns in sector 3 of the Nairobi Securities Exchange	**Reject H_0**
4	There is no effect of own past shocks on volatility of returns in sector 4 of the Nairobi Securities Exchange	**Reject H_0**
5	There is no effect of own past shocks on volatility of returns in sector 5 of the Nairobi Securities Exchange	**Reject H_0**
6	There is no effect of own past shocks on volatility of returns in sector 6 of the Nairobi Securities Exchange	**Reject H_0**
7	There is no effect of own past shocks on volatility of returns in sector 7 of the Nairobi Securities Exchange	**Reject H_0**
8	There is no effect of own past shocks on volatility of returns in sector 8 of the Nairobi Securities Exchange	**Reject H_0**
9	There is no effect of own past shocks on volatility of returns in sector 9 of the Nairobi Securities Exchange	**Reject H_0**
10	There is no effect of own past shocks on volatility of returns in sector 10 of the Nairobi Securities Exchange	**Reject H_0**

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

Source: Study Data (2019)

As per Table 4.11, the study's null hypothesis *i* that *there is no effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya* is strongly

rejected at the 1% level of significance for all NSE sectors. This leads to a failure to reject the alternative hypothesis that *there is an effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya*. The implication is that own shocks to all sectors of the NSE in any week will inevitability elevate the level of volatility in these sectors in the succeeding week.

4.6.1.2 Relationship between Cross Past Shocks and Volatility of Returns

The second objective of this study was to examine the relationship between cross past shocks and volatility in the sectors of the NSE. Essentially, the study sought to find out if the level of volatility in the 10 NSE sectors in any given week is influenced by shocks of other sectors from the preceding week. The second hypothesis of the study, which is replicated below, was tested to accomplish this objective.

Hypothesis ii

H_{02}: There is no effect of cross past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{a2}: There is an effect of cross past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

Hypothesis ii was tested on the basis of Table 4.12. This table shows the estimated off-diagonal coefficients of matrix $\boldsymbol{A}$ together with their respective t statistics and p values. They represent the spillover effects of shocks between all pairs of sectors of the NSE.

Table 4.12: Off-Diagonal Coefficients of Matrix A

		Dependent Variables									
		$\sigma^2_{1,t}$	$\sigma^2_{2,t}$	$\sigma^2_{3,t}$	$\sigma^2_{4,t}$	$\sigma^2_{5,t}$	$\sigma^2_{6,t}$	$\sigma^2_{7,t}$	$\sigma^2_{8,t}$	$\sigma^2_{9,t}$	$\sigma^2_{10,t}$
		j=1	**j=2**	**j=3**	**j=4**	**j=5**	**j=6**	**j=7**	**j=8**	**j=9**	**j=10**
Independent Variables	**Coefficients**										
$\varepsilon^2_{1,t-1}$	a_{1j}		0.045	0.003	0.164***	0.060*	0.075	0.023	0.027	0.033	0.141***
	T-Stat		0.664	0.118	3.393	1.656	1.304	0.463	0.441	0.906	2.927
	P Value		0.507	0.906	0.001	0.098	0.192	0.644	0.659	0.365	0.003
$\varepsilon^2_{2,t-1}$	a_{2j}	0.324***		0.011	0.030	0.030	0.037	0.050	0.087	0.086**	0.008
	T-Stat	6.272		0.325	0.822	0.927	0.729	0.944	1.408	2.012	0.133
	P Value	0.000		0.745	0.411	0.354	0.466	0.345	0.159	0.044	0.894
$\varepsilon^2_{3,t-1}$	a_{3j}	0.130**	0.036		0.039	0.001	0.375***	0.392***	0.195	0.056	0.118
	T-Stat	2.338	0.465		0.700	0.013	4.161	4.520	1.589	0.817	0.822
	P Value	0.019	0.642		0.484	0.990	0.000	0.000	0.112	0.414	0.411
$\varepsilon^2_{4,t-1}$	a_{4j}	0.107***	0.043	0.077**		0.039	0.045	0.053	0.119	0.018	0.170***
	T-Stat	2.658	0.543	2.082		1.044	0.960	1.220	1.264	0.408	4.378
	P Value	0.008	0.587	0.037		0.296	0.337	0.223	0.206	0.683	0.000
$\varepsilon^2_{5,t-1}$	a_{5j}	0.109*	0.113	0.033	0.164*		0.124*	0.349***	0.022	0.357***	0.167**
	T-Stat	1.910	1.222	0.508	1.863		1.899	4.309	0.218	6.134	2.213
	P Value	0.056	0.222	0.611	0.062		0.058	0.000	0.827	0.000	0.027
$\varepsilon^2_{6,t-1}$	a_{6j}	0.033	0.023	0.058	0.135***	0.054		0.269***	0.040	0.292***	0.178***
	T-Stat	0.707	0.341	1.039	2.693	1.102		4.390	0.692	8.015	3.677
	P Value	0.480	0.733	0.299	0.007	0.271		0.000	0.489	0.000	0.000
$\varepsilon^2_{7,t-1}$	a_{7j}	0.010	0.036	0.255***	0.167***	0.035	0.171***		0.209***	0.175***	0.341***
	T-Stat	0.276	0.601	5.037	3.208	1.176	3.569		2.987	4.252	4.906
	P Value	0.783	0.548	0.000	0.001	0.240	0.000		0.003	0.000	0.000
$\varepsilon^2_{8,t-1}$	a_{8j}	0.060**	0.131***	0.085**	0.199***	0.065*	0.041	0.058		0.215***	0.093*
	T-Stat	2.148	3.383	2.425	3.764	1.825	0.827	1.586		6.826	1.789
	P Value	0.032	0.001	0.015	0.000	0.068	0.408	0.113		0.000	0.074
$\varepsilon^2_{9,t-1}$	a_{9j}	0.146***	0.006	0.043	0.088*	0.056	0.022	0.286***	0.100		0.144
	T-Stat	2.795	0.097	1.048	1.696	1.351	0.377	3.608	0.936		1.587
	P Value	0.005	0.923	0.294	0.090	0.177	0.706	0.000	0.349		0.113
$\varepsilon^2_{10,t-1}$	a_{10j}	0.056**	0.011	0.128***	0.190**	0.004	0.132**	0.238***	0.268***	0.122***	
	T-Stat	2.024	0.291	2.497	3.609	0.082	2.344	4.183	4.244	4.223	
	P Value	0.043	0.771	0.013	0.000	0.935	0.019	0.000	0.000	0.000	

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***) and (**) denotes significance at the 1% and 5% level respectively

Source: Study Data (2019)

As per Table 4.12, it can be seen that the Agricultural sector has a bidirectional shock transmission relationship with the Commercial & Services sector (a_{14} = 0.164, a_{41} = 0.107), the Construction & Allied sector (a_{15} = 0.060, a_{51} = 0.109) and the Telecommunications & Technology sector (a_{110} = 0.141, a_{101} = 0.056). The implication is that a shock to the Agricultural sector will have an impact on the next period volatility of the Commercial & Services, Construction & Allied, and Telecommunications & Technology sectors, but on the other hand, the volatility of the Agricultural sector is affected too by the previous week's shocks to the Commercial & Services, Construction & Allied sector, and Telecommunications & Technology sectors.

Lagged shocks to the Automobiles & Accessories sector have a unidirectional effect on the volatility of the Agricultural sector (a_{21} = 0.324) and Manufacturing & Allied Sector (a_{29} = 0.086).

Past shocks to the Banking sector have a unidirectional effect on the volatility of the Agricultural sector (a_{31} = 0.13) and Energy & Petroleum sector (a_{36} = 0.375); and a bidirectional transmission relationship with the Insurance sector (a_{37} = 0.392, a_{73} = 0.255). Therefore, the occurrence of shocks in the banking sector in a certain period will influence the level of next period volatility in the Agricultural and Energy & Petroleum sectors. Moreover, shocks to the banking sector in a given period will influence the volatility of the Insurance sector in the following period, and lagged shocks to the Insurance sector will also have an effect on the banking sector's volatility.

Lagged shocks to the Commercial & Services sector have a unidirectional influence of the volatility of the Banking Sector (a_{43} = 0.077) and the Telecommunications & Technology Sector (a_{410} = 0.170).

Shocks to the Construction & Allied sector have a considerable ability to influence the volatility in other sectors. It is evident that single lagged shocks to this sector do have a unidirectional effect on the volatility of the Commercial & Services sector (a_{54} = 0.164), the Insurance Sector (a_{57} = 0.164), the Energy & Petroleum sector (a_{56} = 0.124), the Manufacturing & Allied sector (a_{59} = 0.357), and the Telecommunications & Technology sector (a_{510} = 0.167).

It is plainly visible that the Energy & Petroleum Sector has a unidirectional shock transmission relationship to the Commercial & Services Sector (a_{64} = 0.357) and the Manufacturing & Allied Sector (a_{69} = 0.178). Therefore, shocks to the Energy & Petroleum Sector in one period will impact the volatility of these two sectors in the following period. Moreover, the Energy & Petroleum Sector has a bidirectional shock transmission linkages with the Insurance Sector (a_{67} = 0.269, a_{76} = 0.171), and the Telecommunications & Technology Sector (a_{610} = 0.178, a_{106} = 0. 0.132). While, shocks of the Energy & Petroleum Sector have an influence on the volatility of both the Insurance and Telecommunications & Technology Sectors; and lagged shocks of these two sectors also affect the volatility of the Energy & Petroleum Sector.

There is a unidirectional shock transmission relationship from the Insurance sector to the Commercial & Services (a_{74} = 0.167) and Investment (a_{78} = 0.209) sectors. Further, the Insurance sector has bidirectional shock transmission linkages with the Manufacturing & Allied Sector (a_{79} = 0.175, a_{97} = 0.286) and the Telecommunications & Technology Sector (a_{710} = 0.341, a_{107} = 0.238).

It can be noticed that the Investment sector is very influential on the volatility of other sectors: There is a unidirectional effect on shocks to this sector on next period volatility in the Agricultural sector (a_{81} = 0.060), the Automobiles & Accessories Sector (a_{82} = 0.131), and the Banking Sector (a_{83} = 0085), the Commercial & Services Sector (a_{84} = 0.199), the Construction & Allied Sector (a_{85} = 0.065) and the Manufacturing & Allied Sector (a_{89} = 0.215). Furthermore, the Investment sector and the Telecommunications & Technology Sector have a bidirectional shock transmission linkage (a_{810} = 0.093, a_{108} = 0.268). Therefore, lagged shocks to the Investment sector have an influence on volatility in the Telecommunications & Technology Sector, while lagged shocks to the Telecommunications & Technology sector have an effect on volatility of the Investment sector too.

The Manufacturing & Allied Sector has unidirectional shock transmission linkages with the Agricultural Sector (a_{91} = 0.146) and the Commercial & Services Sector (a_{94} = 0.088).

Finally, the Telecommunications & Technology Sector is seen to have unidirectional shock transmission relationships to the banking sector (a_{103} = 0.128), the Commercial & Services Sector (a_{104} = 0.190), and the Manufacturing & Allied Sector (a_{109} = 0.122). Table 4.13

summarizes the cross shock transmission relationships that exist between the NSE's sectors. Appendix VI shows the actual sectors between which the cross shock transmission linkages exist.

Table 4.13: Summary of Cross Shock Transmission Relationships

Sector	Influenced Sectors	Influencer Sectors
Agricultural	**3**	**7**
Automobiles & Accessories	**2**	**1**
Banking	**3**	**4**
Commercial & Services	**3**	**7**
Construction & Allied	**6**	**2**
Energy & Petroleum	**4**	**4**
Insurance	**6**	**5**
Investment	**7**	**2**
Manufacturing & Allied	**3**	**6**
Telecommunications & Technology	**7**	**6**

Source: Study Data (2019)

Table 4.13 shows that the Investment and Telecommunications & Technology Sectors are the most influential in terms of the ability of their past shocks to elevate the level of volatility of other sectors in the market. Shocks to these two sectors will reverberate across almost the entire market, since they have a significant influence on the volatility of seven other sectors. On the other hand, the Automobiles & Accessories Sector is least influential, since its shocks affect the volatility of only two other sectors. Table 4.13 also shows that the volatilities of the Agricultural and Commercial & Services sectors are most sensitive to unexpected 'news'

from other sectors. This is because these two sectors' volatility is influenced by the highest number of cross past shocks (7). On the other hand, the volatility of the Automobiles & Accessories Sector is affected by the least number of cross lagged shocks (1).

These findings are in line with Kouki *et al* (2011) who note that shocks to sectors of firms which offer crucial services across the entire economy, such as the Telecommunications & Technology, Investment, and Insurance sectors have a systematic ripple effect due to the scale of their linkages with other sectors. The results are also in line with Ijumba (2013), who finds out that most market sectors in Sub Saharan economies have a higher than average risk profile since their operations are susceptible to the influence of many exogenous factors. Therefore, their sectoral volatilities are very likely to be influenced by cross shocks from other sectors within the same market or even from other stock markets.

The results are also in agreement with Valadkhani, Harvie and Karunanayake (2013) who investigate the dynamics of inter-market transmission of shocks and volatility and posit that shock influences are mainly exerted by the larger sectors onto the smaller sectors. In the present study, lagged shocks to the Telecommunications & Technology, Insurance, and Construction & Allied Sectors, which are among the NSE sectors with the highest capitalization, have a significant impact on the volatility of at least six smaller sectors. The findings disagree with Ewing (2002) who analyzed the shock and volatility transmission interrelationships between five major S&P stock indexes (Capital Goods, Financials, Industrials, Transport and Utilities) and found out that unanticipated shocks in only one sector had a significant impact on other sectors' volatilities; and other four sectors had insignificant cross shock transmission effects. The present study is also in contrast with Majumder and Nag (2018) who conclude that some sectors of the National Stock Exchange of India do not to have any cross shock transmission

relationships with other sectors at all. The results of testing hypothesis *ii* are summarized in Table 4.14.

Table 4.14: Summary of Results of Testing Hypothesis *ii*

Sector	Null Hypothesis	Decision
1	There is no effect of cross past shocks on volatility of returns in sector 1 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
2	There is no effect of cross past shocks on volatility of returns in sector 2 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
3	There is no effect of cross past shocks on volatility of returns in sector 3 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
4	There is no effect of cross past shocks on volatility of returns in sector 4 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
5	There is no effect of cross past shocks on volatility of returns in sector 5 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
6	There is no effect of cross past shocks on volatility of returns in sector 6 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
7	There is no effect of cross past shocks on volatility of returns in sector 7 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
8	There is no effect of cross past shocks on volatility of returns in sector 8 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
9	There is no effect of cross past shocks on volatility of returns in sector 9 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
10	There is no effect of cross past shocks on volatility of returns in sector 10 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

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Source: Study Data (2019)

As per the results in Table 4.14, the study's null hypothesis *ii* that *there is no effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange*, Kenya is rejected that for all sectors of the NSE. This leads to a failure to reject the alternative hypothesis that *there is an effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.* The implication is that volatility of each sector of the NSE in any week is reactive to cross shocks of other sectors from the previous week.

However, all sectors do not have the same level of responsiveness to past cross shocks: The Agricultural and Commercial & Services Sectors have the highest vulnerability to other sectors' past shocks, while the Automobiles & Accessories Sector is least responsive to other sectors' past shocks. In terms of the ability of sectoral lagged shocks to influence other sectors' volatility, the Investment and Telecommunications & Technology Sectors are the most influential sectors, while the Automobiles & Accessories Sector is least influential.

4.6.2 Relationship between Past Volatility and Volatility of Returns

This section entailed testing hypotheses on the persistence of volatility in the NSE's sectors. The estimated coefficients of matrix *B* facilitated the testing of hypotheses whether own volatility in the NSE's sectors is persistent, such that its level in any given week is influenced by its level in the preceding week. Moreover, the tendency of volatility in one sector in a given week to influence the volatility of other sectors in the subsequent weeks, through the volatility spillover effect, was also appraised on the basis of matrix *B*'s estimated coefficients. To enable an orderly discussion of results, the diagonal coefficients of matrix *B* were depicted in Table 4.15 while the off diagonal coefficients of matrix *B* are shown in Table 4.16.

4.6.2.1 Relationship between Own Past Volatility and Volatility of Returns

The third objective of the study was to examine the effect of own past volatility on volatility of each sector of the NSE. In essence, the researcher was interested in finding out whether the volatility of each NSE sector in any given week is influenced by its own level from the previous week. The aim was to investigate the presence of volatility persistence in the NSE's sectors. To attain this objective, the third hypothesis of the study - which is depicted below - was tested.

Hypothesis iii

H_{03}: There is no effect of own past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{a3}: There is an effect of own past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

Hypothesis iii was tested on the basis of the estimated diagonal coefficients of Matrix *B*. These coefficients, together with their respective t statistics and p values are shown in Table 4.15.

Table 4.15: Diagonal Coefficients of Matrix B

		Dependent Variables									
		$\sigma^2_{1,t}$	$\sigma^2_{2,t}$	$\sigma^2_{3,t}$	$\sigma^2_{4,t}$	$\sigma^2_{5,t}$	$\sigma^2_{6,t}$	$\sigma^2_{7,t}$	$\sigma^2_{8,t}$	$\sigma^2_{9,t}$	$\sigma^2_{10,t}$
Independent Variables	**Coefficients**										
$\sigma^2_{1,t-1}$	b_{11}	0.966***									
	T-Stat	11.978									
	P Value	0.000									
$\sigma^2_{2,t-1}$	b_{22}		0.051								
	T-Stat		0.193								
	P Value		0.847								
$\sigma^2_{3,t-1}$	b_{33}			0.847***							
	T-Stat			19.039							
	P Value			0.000							
$\sigma^2_{4,t-1}$	b_{44}				0.134						
	T-Stat				0.629						
	P Value				0.529						
$\sigma^2_{5,t-1}$	b_{55}					0.248					
	T-Stat					0.756					
	P Value					0.450					
$\sigma^2_{6,t-1}$	b_{66}						0.320				
	T-Stat						1.431				
	P Value						0.152				
$\sigma^2_{7,t-1}$	b_{77}							0.751***			
	T-Stat							5.659			
	P Value							0.000			
$\sigma^2_{8,t-1}$	b_{88}								0.714***		
	T-Stat								7.950		
	P Value								0.000		
$\sigma^2_{9,t-1}$	b_{99}									0.823***	
	T-Stat									3.585	
	P Value									0.000	
$\sigma^2_{10,t-1}$	b_{1010}										0.728***
	T-Stat										4.383
	P Value										0.000

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***) and (**) denotes significance at the 1% and 5% level respectively

Source: Study Data (2019)

It can be noticed from Table 4.15 that own past volatility coefficients of the Agricultural, Banking, Insurance, Investment, Manufacturing & Allied, and Telecommunications & Technology sectors are statistically significant. This implies that for these six sectors, there is a high persistence of own past volatility. Therefore, in these sectors, the resulting elevation in volatility after a shock does not dissipate immediately, but it takes a considerable time to decay (Engle and Patton, 2001). In these sectors, the level of volatility in any given week is partly driven by its level from the preceding week, which in return is influenced by the volatility of the week before it.

The Agricultural sector has the highest level of persistence of own volatility (b_{11}= 0.966). This is an indication that in this sector, the rate at which own volatility decays is very low and an almost perfect autocorrelation exists between the levels of volatility witnessed in this sector in any two consecutive weeks. Conversely, the Investment sector has the least level of significant volatility persistence (b_{88}= 0.714). Therefore, volatility in this sector decays off at a higher rate.

On the other hand, persistence of own volatility in the Automobiles & Accessories, Commercial & Services, Construction & Allied, and Energy & Petroleum Sectors is not statistically significant.

The findings are in tandem with Worthington and Higgs (2004) who report that the composition of a sector plays an integral role in influencing its persistence of own sectoral volatility. On average, sectors with more firms listed under them have higher persistence of own volatility *vis-à-vis* sectors with a small number of listed firms. This is due to larger

aggregation of contemporaneous individual-stock volatility persistence effects that are present in sectors with a large number of firms. The study also agrees with Zhang and Jaffry (2015) who conclude that sectors with more mature firms have less persistence of own volatility as compared to sectors with more growth firms. Ostensibly, this is due to the fact that mature sectors derive more of their volatility persistence from cross spillover effects from other sectors, as a results of the cross linkages that they have built over time. On the other hand, the volatility of growth sectors is driven more by its own momentum since such firms are yet to build robust inter-sector linkages, hence they have fewer chances of cross sector spillover of volatility.

These results are also in congruence with Xiao and Dhesi (2010) who suggest that in thinly traded sectors, there are no sufficient volumes to sustain the momentum of own volatility. Therefore, own volatility in such sectors is not persistent and the effects of shocks decay off at a fast rate. Judging by their relatively low levels of mean liquidity (Section 4.2; Table 4.3), it can be inferred that the Automobiles & Accessories, Commercial & Services, Construction & Allied, and Energy & Petroleum sectors are in fact thinly traded - a fact that is in perfectly tandem with the observation in Table 4.15 that own volatility is not persistent in these sectors. The results of testing *hypothesis iii* are summarized in Table 4.16.

Table 4.16: Summary of Results of Testing Hypothesis *iii*

Sector	Null Hypothesis	Decision
1	There is no effect of own past volatility on volatility of returns in sector 1 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
2	There is no effect of own past volatility on volatility of returns in sector 2 of the Nairobi Securities Exchange	**Do not Reject H_0**
3	There is no effect of own past volatility on volatility of returns in sector 3 of the Nairobi Securities Exchange	**Reject H_0**
4	There is no effect of own past volatility on volatility of returns in sector 4 of the Nairobi Securities Exchange	**Do not Reject H_0**
5	There is no effect of own past volatility on volatility of returns in sector 5 of the Nairobi Securities Exchange	**Do not Reject H_0**
6	There is no effect of own past volatility on volatility of returns in sector 6 of the Nairobi Securities Exchange	**Do not Reject H_0**
7	There is no effect of own past volatility on volatility of returns in sector 7 of the Nairobi Securities Exchange	**Reject H_0**
8	There is no effect of own past volatility on volatility of returns in sector 8 of the Nairobi Securities Exchange	**Reject H_0**
9	There is no effect of own past volatility on volatility of returns in sector 9 of the Nairobi Securities Exchange	**Reject H_0**
10	There is no effect of own past volatility on volatility of returns in sector 10 of the Nairobi Securities Exchange	**Reject H_0**

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

Source: Study Data (2019)

Guided by the results in Table 4.16, the study's null hypothesis *iii* that *there is no effect of cross past volatilities on volatility of returns in each sector of the Nairobi Securities*

Exchange, Kenya is rejected for the Agricultural, Banking, Insurance, Investment, Manufacturing & Allied, and Telecommunications & Technology sectors. However, this null hypothesis is not rejected for the Automobiles & Accessories, Commercial & Services, Construction & Allied, and Energy & Petroleum Sectors. Since there is no significant persistence of volatility in these four sectors, the implication is that their level of volatility in any given week is driven primarily by shocks to their returns in the previous week (Engle, 2001).

4.6.2.2 Relationship between Cross Past Volatility and Volatility of Returns

The fourth hypothesis of the study was tested in this section. In this part, results on volatility spillover across the sectors of the NSE are presented. The key issue of interest was to investigate the effect of cross past volatilities from other sectors on the volatility of each NSE sector.

To attain this objective, hypothesis *iv* of the study - which is replicated below - was tested:

H_{04}: There is no effect of cross past volatilities on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{a4}: There is an effect of cross past volatilities on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

To test this hypothesis, the study relied on the results shown in Table 4.17. This Table shows the estimated off-diagonal coefficients of Matrix *B*, together with their respective t statistics and p values. They represent the extant volatility spillover effects between the various pairs of the NSE's sectors.

Table 4.17: Off-Diagonal Coefficients of Matrix *B*

		Dependent Variables									
		$\sigma^2_{1,t}$	$\sigma^2_{2,t}$	$\sigma^2_{3,t}$	$\sigma^2_{4,t}$	$\sigma^2_{5,t}$	$\sigma^2_{6,t}$	$\sigma^2_{7,t}$	$\sigma^2_{8,t}$	$\sigma^2_{9,t}$	$\sigma^2_{10,t}$
		j=1	**j=2**	**j=3**	**j=4**	**j=5**	**j=6**	**j=7**	**j=8**	**j=9**	**j=10**
Independent Variables	**Coefficients**										
$\sigma^2_{1,t-1}$	b_{1j}		0.344***	0.025	0.484***	0.025	0.011	0.032	0.424***	0.343***	0.066
	T-Stat		3.474	0.426	7.118	0.817	0.169	0.410	3.808	3.269	0.859
	P Value		0.001	0.670	0.000	0.414	0.866	0.681	0.000	0.001	0.390
$\sigma^2_{2,t-1}$	b_{2j}	0.365***		0.001	0.118*	0.058	0.022	0.055	0.232	0.065	0.059
	T-Stat	6.050		0.021	1.807	1.409	0.358	0.752	1.196	0.946	0.476
	P Value	0.000		0.983	0.071	0.159	0.721	0.452	0.232	0.344	0.634
$\sigma^2_{3,t-1}$	b_{3j}	0.280***	0.256***		0.181***	0.063	0.602***	0.253	1.141***	0.452***	0.108
	T-Stat	3.937	2.770		3.139	0.438	3.746	1.167	5.441	4.370	0.463
	P Value	0.000	0.006		0.002	0.661	0.000	0.243	0.000	0.000	0.644
$\sigma^2_{4,t-1}$	b_{4j}	0.445***	0.339***	0.058		0.322**	0.303**	0.347	0.051	0.176	0.048
	T-Stat	7.613	3.469	1.445		2.177	2.068	1.632	0.383	1.289	0.733
	P Value	0.000	0.001	0.148		0.029	0.039	0.103	0.702	0.197	0.464
$\sigma^2_{5,t-1}$	b_{5j}	0.004	0.052	0.476***	0.720***		0.418***	0.173	0.395**	0.241***	0.013
	T-Stat	0.050	0.356	7.204	6.592		4.357	0.950	2.075	3.196	0.091
	P Value	0.961	0.722	0.000	0.000		0.000	0.342	0.038	0.001	0.928
$\sigma^2_{6,t-1}$	b_{6j}	0.023	0.045	0.171	0.655***	0.096		0.115***	0.234***	0.480***	0.481***
	T-Stat	0.225	0.255	1.432	11.515	1.088		3.332	3.395	8.646	12.382
	P Value	0.822	0.798	0.152	0.000	0.277		0.001	0.001	0.000	0.000
$\sigma^2_{7,t-1}$	b_{7j}	0.231***	0.035	0.085	0.178*	0.246**	0.526***		0.123	0.065	0.260
	T-Stat	4.285	0.396	0.570	1.794	2.115	4.286		1.308	1.071	1.395
	P Value	0.000	0.692	0.569	0.073	0.034	0.000		0.191	0.284	0.163
$\sigma^2_{8,t-1}$	b_{8j}	0.039	0.232	0.033	0.231**	0.069	0.253***	0.053		0.169***	0.190
	T-Stat	0.556	1.638	0.351	2.556	0.968	3.494	1.237		3.307	1.132
	P Value	0.578	0.101	0.726	0.011	0.333	0.000	0.216		0.001	0.258
$\sigma^2_{9,t-1}$	b_{9j}	0.211***	0.673***	0.153**	0.305***	0.172**	0.107	0.224*	0.072		0.111
	T-Stat	2.770	8.555	2.414	3.041	2.315	0.856	1.937	0.788		1.003
	P Value	0.006	0.000	0.016	0.002	0.021	0.392	0.053	0.431		0.316
$\sigma^2_{10,t-1}$	b_{10j}	0.010	0.040	0.121	0.018	0.015	0.034	0.394***	0.268	0.049	
	T-Stat	0.251	0.591	1.629	0.436	0.377	0.486	4.548	1.329	0.867	
	P Value	0.802	0.555	0.103	0.663	0.706	0.627	0.000	0.184	0.386	

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***) and (**) denotes significance at the 1% and 5% level respectively

Source: Study Data (2019)

It is evident from Table 4.17 that there are bidirectional volatility spillover linkages between the Agricultural sector and the Automobiles & Accessories Sector (b_{12} = 0.344, b_{21} = 0.365), the Commercial & Services Sector (b_{14} = 0.484, b_{41} = 0.445), and the Manufacturing & Allied Sector (b_{19} = 0.343, b_{91} = 0.211). The results mean that the volatility in the Agricultural sector in any given week will influence the volatility of these three sectors in the succeeding week. Conversely, the volatility of the Automobiles & Accessories, Commercial & Services, and Manufacturing & Allied Sectors also informs the volatility of the Agricultural sector. Moreover, there is unidirectional volatility spillover from the Agricultural sector to the Investment sector (b_{18} = 0.424). This implies that the volatility in the Agricultural sector in any given week has a causal influence on the volatility of the Investment sector in the succeeding week.

The findings further indicate the presence of a bidirectional volatility spillover linkage between the Automobiles & Accessories Sector and the Commercial & Services Sector (b_{24} = 0.118, b_{42} = 0.339). The implication is that the volatility of the Automobiles & Accessories Sector in any given week has a causative effect on the volatility of the Commercial & Services Sector in the following week. Likewise, the volatility of the Commercial & Services Sector in a given week will influence the volatility of the Automobiles & Accessories Sector in the following week.

The essence of the Banking sector, in terms of its interrelatedness with other market sectors is clearly apparent. This is due to the fact that the volatility of this sector in any given week has a unidirectional causal influence on the volatility of five other sectors in the succeeding week, and only one bidirectional volatility spillover linkage. Volatility of the banking sector

spillovers over unidirectionally to the Agricultural Sector (b_{31} = 0.280), the Automobiles & Accessories Sector (b_{32} = 0.256), the Commercial & Services Sector (b_{34} = 0.181), the Energy & Petroleum Sector (b_{36} = 0.602), and the Investment Sector (b_{38} = 1.141). Moreover, there is bidirectional spillover of volatility between the Banking sector and the Manufacturing & Allied Sector (b_{39} = 0.452, b_{93} = 0.153).

There is evidence of unidirectional spillover of volatility from the Commercial & Services Sector to the Automobiles & Accessories Sector (b_{42} = 0.339). This means that volatility of the Commercial & Services in any given week has a causative influence on the volatility of the Automobiles & Accessories Sector in succeeding week. However, volatility of the Automobiles & Accessories Sector does not have any causal effect on the Commercial & Services sector. Further, there is bidirectional transmission of volatility between the Commercial & Services Sector and the Construction & Allied Sector (b_{45} = 0.322, b_{54} = 0.720) as well as the Energy & Petroleum Sector (b_{46} = 0.303, b_{64} = 0.655). The implication is that the volatility of the Commercial & Services Sector in a given week informs the volatility of the Construction & Allied Sector and Energy & Petroleum Sector in the succeeding week. Likewise, lagged volatilities of the Energy & Petroleum and Construction & Allied Sectors affect the Commercial & Services Sector's volatility.

The results further confirm the presence of unidirectional volatility spillover linkages from the Construction & Allied Sector to the Banking sector (b_{53} = 0.476), the Energy & Petroleum Sector (b_{56} = 0.418), and the Investment Sector (b_{58} = 0.395). Moreover, there is

evidence of a bidirectional volatility transmission relationship between the Construction & Allied Sector and the Manufacturing & Allied Sector (b_{59} = 0.241, b_{95} = 0.172).

The Energy & Petroleum Sector has bidirectional volatility spillover relationships with the Insurance Sector (b_{67} = 0.115, b_{76} = 0.526) and the Investment sector (b_{68} = 0.234, b_{86} = 0.253). Moreover, the Energy & Petroleum sector transmits its volatility unidirectionally to the Manufacturing & Allied Sector (b_{69} = 0.480) and the Telecommunications & Technology Sector (b_{610} = 0.481).

Lagged volatility of the Insurance sector has a unidirectional effect on the volatility of the Agricultural Sector (b_{71} = 0.231), the Commercial & Services Sector (b_{74} = 0.178), and the Construction & Allied Sector (b_{75} = 0.246).

It is evident that volatility of the Investment sector in a given week unidirectionally affects the volatility of the Commercial & Services (b_{84} = 0.231) and Manufacturing & Allied (b_{89} = 0.169) Sectors.

Finally, it can be inferred that volatility of the Insurance sector is affected unidirectionally by lagged volatility from the Manufacturing & Allied sector (b_{97} = 0.224) and the Telecommunications & Technology Sectors (b_{107} = 0.394).

The cross sector volatility transmission relationships that are present within the sectors of the NSE are summarized in Table 4.18. The full cross volatility transmission linkages of all NSE's sectors are presented in Appendix VII.

Table 4.18: Summary of Cross Volatility Transmission Relationships

Sector	Influenced Sectors	Influencer Sectors
Agricultural	**4**	**5**
Automobiles & Accessories	**2**	**4**
Banking	**6**	**2**
Commercial & Services	**4**	**8**
Construction & Allied	**5**	**3**
Energy & Petroleum	**5**	**5**
Insurance	**4**	**3**
Investment	**3**	**4**
Manufacturing & Allied	**6**	**5**
Telecommunications & Technology	**1**	**1**

Source: Study Data (2019)

Table 4.18 shows that single-lagged volatility of the Banking, Manufacturing & Allied, Construction & Allied, and Energy & Petroleum Sectors have the largest tendency to influence the volatility of other sectors. The volatility of both the Banking and Manufacturing & Allied Sectors in any given week causally influences the volatility of 6 other sectors in the succeeding week, while volatility of the Construction & Allied and Energy & Petroleum Sectors in any given period influences the volatility of 5 other sectors each in the next period. On the other hand, volatility of the Telecommunications & Technology Sector has the least tendency to affect next-period volatility of other sectors, since this sector has only one such linkage.

Tables 4.18 also show that the Commercial & Services sector is very vulnerable to contagion flows, since its volatility is reactive to cross spillovers of lagged volatility from eight other NSE sectors. In fact, from Table 4.17 it can be seen that the volatility of this sector is influenced by the lagged volatility of all other sectors of the NSE, except the Telecommunications & Technology Sector. On the other hand, the Telecommunications & Technology Sector is deemed to be the most robust sector, in terms of withstanding the influence of cross volatility spillovers from other sectors. This is inferred from the fact that its volatility is affected by contagion flows from only one sector (Insurance sector).

These findings are in congruence with Minderhoud (2003) who suggests that inter-sector volatility spillovers mostly originate from vital sectors that avail crucial services and goods to firms in other sectors. In many cases, the products of the vital sectors are input variables in the operations of other sectors. Therefore, any uncertainty in the crucial sectors stimulates volatility in other market sectors, due to the potential of systematic disruptions to occur in almost the entire market in case the crucial sectors get into a crisis. For instance, the Banking and Energy & Petroleum Sectors of the NSE are key to the smooth operations of other sectors. Therefore it's unsurprising that lagged volatility in these sectors has a causal influence on the volatility of most of other sectors.

These results further agree with those of Hassan and Malik (2007) who found evidence of cross sector spillover of volatility in six S&P stock indexes. The study is also in tandem with Karmakar (2010) who found out bidirectional volatility spillover patterns between indexes of large capitalization and small capitalization equities listed on the National Stock Exchange of India.

The findings additional concur with Kuttu (2014) who found that volatility of the Nigerian all share market index influences volatility of the Ghanaian, Kenyan and South African all stock market indexes. Finally, this research is in tandem with Chinzara and Aziakpono (2014) who established that volatilities of the Australian, Chinese and American all share market indexes have a significant influence on the volatility of the South African all stock index. Table 4.19 summarizes the results of testing hypothesis *iv*.

Table 4.19: Summary of Results of Testing Hypothesis *iv*

Sector	Null Hypothesis	Decision
1	There is no effect of cross past volatility on volatility of returns in sector 1 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
2	There is no effect of cross past volatility on volatility of returns in sector 2 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
3	There is no effect of cross past volatility on volatility of returns in sector 3 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
4	There is no effect of cross past volatility on volatility of returns in sector 4 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
5	There is no effect of cross past volatility on volatility of returns in sector 5 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
6	There is no effect of cross past volatility on volatility of returns in sector 6 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
7	There is no effect of cross past volatility on volatility of returns in sector 7 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
8	There is no effect of cross past volatility on volatility of returns in sector 8 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
9	There is no effect of cross past volatility on volatility of returns in sector 9 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
10	There is no effect of cross past volatility on volatility of returns in sector 10 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

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Source: Study Data (2019)

As per Table 4.19, the study's null hypothesis *iv* that *there is no effect of cross past volatility on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya* is rejected

with respect to each NSE sector. The implication is that the level of volatility of each sector of the NSE in any given week is partly influenced by the level of volatility of at least one of other NSE sectors in the preceding week. However, the scale of sectoral receptiveness to lagged volatility is not uniform: The Commercial & Services Sector is most responsive to other NSE sectors' lagged volatilities, since it is susceptible to contagion flows from eight other sectors. Conversely, the Telecommunications & Technology Sector is most resilient since its volatility is influenced by the lagged cross volatility of only one other sector. Furthermore, the Manufacturing & Allied and Banking Sectors are deemed to be most influential, since turbulence in each of these two sectors causes the heightening of volatility in six other sectors. Finally, the Telecommunications & Technology Sector is deduced to be least influential in the sense that its lagged volatility has an effect on the volatility of only one other NSE sector.

4.7 Testing for Multivariate Residual Autocorrelation

Bauwens *et al* (2006) advise that after fitting MGARCH models, testing for residual autocorrelation should be taken undertaken as a post estimation procedure. This procedure verifies whether the standardized multivariate residuals of fitting the variance equation are autocorrelated or not. Autocorrelation of standardized residuals would imply that the model is not correctly specified and/or it does not have the required goodness of fit for the study's data. Brooks (2008) concurs and notes that the standardized residuals of a multivariate GARCH model which has an apt goodness of fit should be identically and independently distributed, and each one of them should be a white noise process with a mean of zero and unit variance. The Multivariate Ljung-Box Q Test was used to test the residuals of the multivariate GARCH model for residual autocorrelation. This test is based on the null hypothesis that the residual are not autocorrelated, against the alternative hypothesis that the

residuals are autocorrelated. The null hypothesis should be rejected if the p value is lower than the critical value of 5%. The results of the multivariate Ljung-Box Q test are shown in Table 4.20.

Table 4.20: Multivariate Ljung-Box Q Test for Residual Autocorrelation

Test Run Over	Lags Tested	Degrees of Freedom	Q Statistic	P value
3 to 555	5	80	78.45029	0.5281

Source: Study Data (2019)

As evident in Table 4.20, the p value of the Multivariate Ljung-Box Q Test was not significant upto 5 lags. Therefore, the null hypothesis of no residual autocorrelation was not rejected and the residuals were deemed to be white noise processes. This affirms that the fitted multivariate GARCH model was correctly specified and it had the required goodness of fit.

4.8 Testing for Moderating Effect of Liquidity

The fifth objective of this study was to appraise the moderating effect of liquidity on the relationship between own past shocks and own past volatility on the current volatility of each sector of the NSE. The main issue of interest here was to find out whether the tendency of a NSE sector's volatility in any given week to be influenced by its own volatility and shocks from the previous week is moderated by the prevailing level of liquidity in this (previous) week. In this part, hypothesis *v* of the study - which is replicated below - was tested.

H_{05}: There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

H_{a5}: There is a moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of returns in each sector of the Nairobi Securities Exchange, Kenya.

Since there were no inter-sector relationships that were being investigated in this part, the study used univariate GARCH models to test this hypothesis. A two step methodology, which was proposed by Irwin and McClelland (2001), was used to test for the moderating effect of liquidity on the relationship between past own shocks and past own volatility and current volatility. In step one, 10 univariate GARCH (1,1) models were fitted to estimate the volatility of each sector as a function of its own past shocks and own past volatility. These were the base models for testing the moderating effect and they were fitted so as to investigate whether volatility of each sector in each week is indeed dependent on the previous week's own shocks and persistent own volatility.

In the second step, the 10 GARCH (1,1) models were fitted again, but now with three additional exogenous variance regressors in each - a single lag of the moderator variable and two interaction terms that were computed by multiplying the lagged moderator variable with: lagged squared residuals (interaction term one) and the lagged moderator variable with lagged variance of residuals (interaction term two).

Following the Helm and Mark (2012) criteria, it should be concluded that the level of prevailing liquidity in any given week moderates the relationship between this week's shocks

& volatility and the volatility of the succeeding period if the coefficients of the interaction terms in the interaction model are statistically significant. Moreover, the coefficients of determination (R^2) of the interaction models should be higher than those of their corresponding base models if the moderating effect is present.

4.8.1 Step one of testing the Moderating Effect of Liquidity: Fitting the Base Models

In step one of testing the moderating effect of liquidity, base models for the NSE's 10 sectors were fitted using the univariate GARCH (1,1) specification. Each base model had the functional form of equation 3.17, as described in section 3.5.1. Diagnostic tests were first conducted to ensure that the requirements of fitting conditional volatility models are met. Next, the univariate GARCH (1,1) models were fitted and their results discussed. Finally, post estimation diagnostic testing was conducted to assure that the standardized residuals had no autocorrelation, thereby implying a proper goodness of fit.

4.8.1.1 Diagnostic Tests

Before fitting univariate GARCH (1,1) models, the sectoral returns data for each sector must be stationary. Furthermore, the squares of the univariate mean equations' residuals must exhibit autocorrelation (ARCH effects). Diagnostic testing in this section entailed recalling of results of the previous conducted tests for stationarity and undertaking the univariate tests for ARCH effects.

Testing for Stationarity - The ADF and KPSS tests were used to test the 10 returns series for stationarity. These tests were conducted in section 4.4.1 and their results presented in Tables 4.4 and 4.5. In that section, the results of the ADF tests showed that the null hypothesis of a unit root is rejected for all returns series at the 1% level of significance.

Moreover, the KPSS tests indicated that the null hypothesis of stationarity could not rejected for all series at the 1% level of significance. Therefore, there was consensus from the ADF and KPSS tests that all returns series were stationary at levels and could therefore be utilized for analysis without any transformation.

Testing for Univariate ARCH Effects - If a time series exhibits ARCH effects, the squared residuals of estimating this series as an autoregressive model of order one must exhibit autocorrelation, thereby implying the presence of volatility clustering. In such a series, and the level of volatility in any given period is influenced by the shocks (squared residuals) of the previous period. In order to estimate a GARCH (1,1) model, ARCH effects must be present in the pertinent time series. In this study, the Engle LM test was used to test for univariate ARCH effects in each of the 10 returns series. The null hypothesis of this test is that ARCH effects are not present, upto a definite lag while the alternative hypothesis is that ARCH effects are present, upto the same lag. Results of the Engle LM test for ARCH effects are shown in Table 4.21.

Table 4.21: Engle LM test for Univariate ARCH Effects

Sectoral Returns Series	F-statistic	P Value: F(5,541)	Obs*R-squared	P Value: Chi-Square(5)
Agricultural	4.18293	0.00100	20.35953	0.00110
Automobiles & Accessories	7.10304	0.00000	33.69685	0.00000
Banking	3.35989	0.00530	16.4742	0.00560
Commercial & Services	3.99709	0.00849	20.13271	0.00847
Construction & Allied	4.13601	0.00531	20.75071	0.00528
Energy & Petroleum	6.07615	0.00301	30.37651	0.00299
Insurance	8.44136	0.00000	39.58653	0.00000
Investment	3.36213	0.00530	16.48485	0.00560
Manufacturing & Allied	5.58844	0.00924	26.17916	0.00923
Telecommunications & Technology	8.28442	0.00000	38.90287	0.00000

Source: Study Data (2019)

Since the p values are all less than 1%, the null hypothesis that ARCH effects are not present was rejected at the 1% level of significance for all returns series. The conclusion from the Engle ARCH-LM tests is that univariate ARCH effects were present in all 10 returns series.

4.8.1.2 Results of Fitting the Base Models

After verifying that the raw data was stationary and that ARCH effects were present in the returns data of all 10 sectors, the study fitted the base models for testing the moderating effect of liquidity using the GARCH (1,1) specification. The 10 base models were fitted as per equation 3.17, and the full output of this procedure is depicted in Appendix VIII. Table 4.22 outlines a summary of the key results of fitting the base models.

Table 4.22: Summary Results of Fitting the Base Models

		Sector									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Intercept										
	cv_i										
	(*i* =1,2,…,10)	0.010***	0.003***	0.013***	0.028***	0.009**	0.007**	0.06***	0.001***	0.001***	0.088**
	Z-Stat	8.8954	4.610	3.238	4.700	2.115	2.510	6.700	4.356	19.022	2.330
	P Value	0.000	0.000	0.001	0.000	0.030	0.012	0.000	0.000	0.000	0.020
Variance Regressors	**Coefficients**										
$\varepsilon_{i,t-1}^2$	α_i										
(*i* =1,2,…,10)	**(*i* =1,2,…,10)**	0.0417***	0.204***	0.161***	0.039***	0.023	0.055***	0.33***	0.214***	0.121***	0.001
	Z-Stat	9.726	4.8181	3.457	4.760	0.954	3.224	5.297	3.849	2.935	0.007
	P Value	0.000	0.000	0.001	0.000	0.340	0.001	0.000	0.000	0.003	0.885
$\sigma_{i,t-1}^2$	γ_i										
(*i* =1,2,…,10)	**(*i* =1,2,…,10)**	0.9312***	0.580***	0.622***	0.916***	0.819***	0.884***	0.233***	0.494***	0.132***	0.988***
	Z-Stat	18.901	8.122	6.119	112.010	4.454	25.997	2.861	4.889	3.425	114.294
	P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.000
Coefficient of Determination (R^2)		0.009708	0.000167	0.023197	0.015315	0.006603	0.001119	0.011356	0.001708	0.0017010	0.005547

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)

Table 4.22 shows strong relationships between the dependent variable and the independent variables in the GARCH (1,1) models. In all 10 equations, only two GARCH (1,1) equations (for the Telecommunications & Technology and Construction & Allied sectors) had an insignificant coefficient for the variance equation. In both cases, the insignificant coefficient was for the lag of squared residuals. All coefficients for the other eight models were statistically significant.

4.8.1.3 Testing for Univariate Residual Autocorrelation – Base Models

After fitting each base model, the standardized residuals were tested for autocorrelation. This was to preclude the problem of model inadequacy or misspecification that would be existent in case any autocorrelation was detected in the standardized residuals. For each model, univariate Ljung-Box Q tests were conducted on standardized residuals upto a maximum of 5 lags. Results of these tests are depicted in Table 4.23.

Table 4.23: Univariate Ljung-Box Q Tests for Residual Autocorrelation

Model	Maximum Lag	Q-Stat	Prob
Agricultural	5	3.424	0.635
Automobiles & Accessories	5	1.480	0.915
Banking	5	8.845	0.115
Commercial & Services	5	6.332	0.275
Construction & Allied	5	6.745	0.240
Energy & Petroleum	5	6.091	0.297
Insurance	5	6.574	0.254
Investment	5	4.426	0.490
Manufacturing & Allied	5	2.427	0.787
Telecommunications & Technology	5	1.143	0.950

Source: Study Data (2019)

For all 10 models, the p values of the Ljung-Box Q tests were not statistically significant. Therefore, the null hypothesis of no autocorrelation was not rejected for all cases. Consequently, all 10 univariate GARCH (1,1) models were deemed to be correctly specified with apt goodness of fit.

4.8.2 Step Two of testing the Moderating Effect: Fitting the Interaction Models

In step two of testing for the moderating effect of liquidity, the analysis carried out in step one was replicated, but with the moderating variable and the interaction terms being included as exogenous variables in the variance equations (Irwin and McClelland (2001; Mark and Helm, 2012). Essentially, this entailed fitting of the interaction model for each sector as per equation 3.22 which is described in section 3.5.2.3. For each interaction model, there were three exogenous variance regressors. The first one was the liquidity series for the respective sector, taken at a single lag. The second exogenous variable was the product of a single lag of own shocks series and a single lag of the liquidity series. The final exogenous variable was the product of a single lag of own volatility series and a single lag of the liquidity series. The first exogenous variance regressor was the moderating variable while the last two were the interaction terms of the variance equation's independent variables and the moderating variable.

For each sector, the time series data for the moderator was computed as per equation 3.18 of section 3.4.5. Moreover, the interaction terms were computed as a product of the first lag of each variance model's independent variables and the first lag of the moderating variable as per equations 3.19 and 3.20. This is elucidated in Table 4.24.

Table 4.24: Summary of Moderating Variable Series and Interaction Terms

	Sector									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Moderating Variable									
Liquidity of sector *i* for week *t-1* (i = 1,2,…,10)	$\omega_{1,t-1}$	$\omega_{2,t-1}$	$\omega_{3,t-1}$	$\omega_{4,t-1}$	$\omega_{5,t-1}$	$\omega_{6,t-1}$	$\omega_{7,t-1}$	$\omega_{8,t-1}$	$\omega_{9,t-1}$	$\omega_{10,t-1}$
	Interaction Terms									
Liquidity of sector *i* for week *t-1** Shock of sector *i* for week *t-1* (i = 1,2,…,10)	$IT_{s1,t-1}$	$IT_{s2,t-1}$	$IT_{s3,t-1}$	$IT_{s4,t-1}$	$IT_{s5,t-1}$	$IT_{s6,t-1}$	$IT_{s7,t-1}$	$IT_{s8,t-1}$	$IT_{s9,t-1}$	$IT_{s10,t-1}$
Liquidity of sector *i* for week *t-1** Volatility of sector *i* for week *t-1* (i = 1,2,…,10)	$IT_{v1,t-1}$	$IT_{v2,t-1}$	$IT_{v3,t-1}$	$IT_{v4,t-1}$	$IT_{v5,t-1}$	$IT_{v6,t-1}$	$IT_{v7,t-1}$	$IT_{v8,t-1}$	$IT_{v9,t-1}$	$IT_{v10,t-1}$

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

Source: Study Data (2019)

Table 4.24 summarizes the liquidity and interaction terms variables that were utilized in this section as exogenous variance regressors in the univariate interaction models.

4.8.2.1 Diagnostic Testing

Having confirmed earlier that the sectoral returns were stationary (section 4.4.1; Tables 4.4 and 4.5) and that univariate ARCH effects were present in these returns (section 4.8.1.1; Table 4.21), it was only necessary to test for stationarity of the moderating variable and the interaction terms in this section.

Testing for Stationarity - The study sought to assure that the liquidity series and interaction terms series that were utilized as exogenous variables in the variance equations when fitting the interaction models were stationary. ADF and KPSS tests were utilized in this feat. Table 4.25 shows the results for the ADF tests for the liquidity variable and interaction terms.

Table 4.25: ADF Tests for Moderating Variable and Interaction Terms

	Sector									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Moderating Variable									
Lagged Liquidity	$\omega_{1,t-1}$	$\omega_{2,t-1}$	$\omega_{3,t-1}$	$\omega_{4,t-1}$	$\omega_{5,t-1}$	$\omega_{6,t-1}$	$\omega_{7,t-1}$	$\omega_{8,t-1}$	$\omega_{9,t-1}$	$\omega_{10,t-1}$
ADF Test Statistic	-11.349	-8.3515	-4.8834	-18.776	-12.821	-3.7213	-19.5	-4.8578	-5.1058	-13.312
	Interaction Terms									
Lagged Liquidity* Lagged Shock	$IT_{s1,t-1}$	$IT_{s2,t-1}$	$IT_{s3,t-1}$	$IT_{s4,t-1}$	$IT_{s5,t-1}$	$IT_{s6,t-1}$	$IT_{s7,t-1}$	$IT_{s8,t-1}$	$IT_{s9,t-1}$	$IT_{s10,t-1}$
ADF Test Statistic	-16.823	-21.595	-20.729	-21.87	-22.587	-20.843	-22.254	-22.733	-18.15	-22.926
Lagged Liquidity* Lagged Volatility	$IT_{v1,t-1}$	$IT_{v2,t-1}$	$IT_{v3,t-1}$	$IT_{v4,t-1}$	$IT_{v5,t-1}$	$IT_{v6,t-1}$	$IT_{v7,t-1}$	$IT_{v8,t-1}$	$IT_{v9,t-1}$	$IT_{v10,t-1}$
ADF Test Statistic	-12.983	-16.281	-18.537	-19.11	-18.553	-16.571	-17.678	-11.317	-18.222	-16.541
ADF Critical Values	1% Critical Value: -3.43 5% Critical Value: -2.86 10% Critical Value: -2.57									

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

Source: Study Data (2019)

Results of the ADF tests indicated that for all 10 liquidity series and 20 interaction terms series, the null hypothesis of a unit root was rejected at all levels of significance. This can be inferred from the fact that each of the 30 ADF test statistics was less than the three critical

values. Therefore, all 30 series were deemed to be stationary at levels at the 1% level of significance. The study further utilized KPSS tests to triangulate the results of the ADF tests. This was done in order to assure the stationarity of the 30 time series further. The results of the KPSS tests are shown in Table 4.26.

Table 4.26: KPSS Tests for Moderating and Interaction Terms Series

	Sector									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Moderating Variable									
Lagged Liquidity	$\omega_{1,t-1}$	$\omega_{2,t-1}$	$\omega_{3,t-1}$	$\omega_{4,t-1}$	$\omega_{5,t-1}$	$\omega_{6,t-1}$	$\omega_{7,t-1}$	$\omega_{8,t-1}$	$\omega_{9,t-1}$	$\omega_{10,t-1}$
KPSS Test Statistic	0.041	0.081	0.048	0.066	0.067	0.040	0.032	0.108	0.059	0.020
	Interaction Terms									
Lagged Liquidity * Lagged Shock	$ITs_{1,t-1}$	$ITs_{2,t-1}$	$ITs_{3,t-1}$	$ITs_{4,t-1}$	$ITs_{5,t-1}$	$ITs_{6,t-1}$	$ITs_{7,t-1}$	$ITs_{8,t-1}$	$ITs_{9,t-1}$	$ITs_{10,t-1}$
KPSS Test Statistic	0.059	0.108	0.037	0.082	0.041	0.099	0.078	0.093	0.040	0.096
Lagged Liquidity * Lagged Volatility	$ITv_{1,t-1}$	$ITv_{2,t-1}$	$ITv_{3,t-1}$	$ITv_{4,t-1}$	$ITv_{5,t-1}$	$ITv_{6,t-1}$	$ITv_{7,t-1}$	$ITv_{8,t-1}$	$ITv_{9,t-1}$	$ITv_{10,t-1}$
KPSS Test Statistic	0.084	0.030	0.108	0.071	0.075	0.034	0.111	0.051	0.055	0.073
KPSS Critical Values	1% Critical Value: 0.216 5% Critical Value: 0.146 10% Critical Value: 0.119									

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

Source: Study Data (2019)

Table 4.26 shows that all KPSS test statistics were less than their respective critical values for all three levels of significance. These results are in coherence with the ADF tests results since they imply that the null hypothesis of stationarity must not be rejected at all levels of

significance. Therefore, the 10 liquidity series and 20 interaction terms series that were utilized in this section were deemed to be stationarity.

4.8.2.2 Results of Fitting the Interaction Models

Having verified that the exogenous variables to be utilized in this section were stationary and that univariate ARCH effects were present in each of the sectoral returns, 10 interaction models were fitted - using the functional form of equation 3.22 - as univariate GARCH (1,1) models with 3 exogenous variance regressors (moderating variable and two interaction terms) each. Table 4.27 shows a summary of these results. The full results of fitting the interaction models are outlined in Appendix IX.

Table 4.27: Summary Results of Fitting the Interaction Models

		Sector									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Intercept											
	CV_i										
	(i =1,2,…,10)	0.013***	0.009	0.016***	0.011**	0.029	0.033***	0.058***	0.049**	0.013*	0.02***
	Z-Stat	6.950	0.726	2.789	2.521	1.218	3.854	4.381	2.927	1.732	3.031
	P Value	0.000	0.468	0.005	0.012	0.223	0.000	0.000	0.003	0.083	0.002
Variance Regressors	**Coefficients**										
$\varepsilon^2_{i,t-1}$	α_i										
(i =1,2,…,10)	**(i =1,2,…,10)**	0.190***	0.27***	0.189***	0.24***	0.023	0.151**	0.348***	0.189***	0.391***	0.032
	Z-Stat	6.050	6.117	3.680	4.122	0.551	2.339	5.239	3.527	6.337	1.582
	P Value	0.000	0.000	0.000	0.000	0.582	0.019	0.000	0.000	0.000	0.114
$\sigma^2_{i,t-1}$	γ_i										
(i =1,2,…,10)	**(i =1,2,…,10)**	0.621***	0.325***	0.511***	1.04***	0.484	0.254**	0.268***	0.568***	0.294***	0.88***
	Z-Stat	17.527	4.889	4.555	9.218	1.163	2.015	3.309	5.006	5.092	34.894
	P Value	0.000	0.000	0.000	0.000	0.245	0.044	0.001	0.000	0.000	0.000
$\omega_{i,t-1}$	ν_i										
(i =1,2,…,10)	**(i =1,2,…,10)**	0.049***	0.975***	0.021	0.019***	-0.015	0.329***	-0.037	0.041	0.208***	-0.032
	Z-Stat	3.432	9.731	1.101	5.001	-1.536	3.499	-0.653	0.058	5.726	-1.275
	P Value	0.001	0.000	0.271	0.000	0.125	0.001	0.514	0.954	0.000	0.202
$IT_{si,t-1}$	λ_i										
(i =1,2,…,10)	**(i =1,2,…,10)**	0.006***	0.003***	0.021***	0.013***	0.054	0.029***	0.071*	0.055***	0.027***	0.02***
	Z-Stat	2.724	11.739	3.237	3.307	0.050	8.352	1.904	2.684	8.499	4.216
	P Value	0.006	0.000	0.001	0.001	0.960	0.000	0.057	0.007	0.000	0.000
$IT_{vi,t-1}$	ϕ_i										
(i =1,2,…,10)	**(i =1,2,…,10)**	0.003***	0.078***	0.002	0.033***	-0.014	0.015**	-0.048	0.011	0.046	0.040
	Z-Stat	6.775	4.310	0.217	13.821	-0.195	2.058	-1.584	0.001	1.495	1.620
	P Value	0.000	0.000	0.828	0.000	0.846	0.040	0.113	0.999	0.135	0.105
Coefficient of Determination (R^2)		0.01423	0.001326	0.02135	0.02053	0.00594	0.00013	0.01072	0.00159	0.00057	0.00460

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories Sector
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 is Telecommunications & Technology Sector

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)

It can be noticed from Table 4.27 that volatility of the Agricultural sector is affected significantly by all predictor variables, including the moderating variable and the interaction terms. For the Automobiles & Accessories sector, all variance regressors have a significant effect on volatility, but the intercept coefficient isn't significant. On the model for the banking sector, it can be seen that the single lag of liquidity ($\omega_{3,t-1}$) and the $IT_{v3,t-1}$ interaction term are not statistically significant. All variance regressors of the Commercial & Services sector have a significant effect on this sector's volatility, while in the Construction & Allied sector; all six relationships between volatility and its regressors are statistically insignificant.

There is a significant effect of all regressors on the volatility of the Energy & Petroleum sector. For the insurance sector, the effect of the single lag of liquidity ($\omega_{7,t-1}$) and the $IT_{v7,t-1}$ interaction term on volatility is not significant. Likewise, for the Investment sector, the coefficients of the single lag of liquidity ($\omega_{8,t-1}$) and the $IT_{v8,t-1}$ interaction term are not statistically significant. For the Manufacturing & Allied sector, interaction term $IT_{v9,t-1}$ does not have a significant effect on volatility, while in the Telecommunications & Technology sector, both single lag of liquidity ($\omega_{10,t-1}$) and interaction term $IT_{v10,t-1}$ are not statistically significant.

4.8.2.3 Testing for Univariate Residual Autocorrelation - Interaction Models

After fitting each interaction model, the standardized residuals were tested for autocorrelation. This was to preclude the problem of model inadequacy or misspecification that would be existent in case any autocorrelation was detected in the standardized residuals. For each model, univariate Ljung-Box Q tests were computed on standardized residuals upto a maximum of 5 lags. Results of these tests are depicted in Table 4.28.

Table 4.28: Testing for Univariate Residual Autocorrelation - Interaction Models

Model	Maximum Lag	Q-Stat	Prob
Agricultural	5	3.5867	0.611
Automobiles & Accessories	5	1.5477	0.907
Banking	5	8.1503	0.148
Commercial & Services	5	6.4108	0.268
Construction & Allied	5	6.2271	0.285
Energy & Petroleum	5	6.1031	0.248
Insurance	5	6.7298	0.242
Investment	5	3.1996	0.669
Manufacturing & Allied	5	2.3258	0.802
Telecommunications & Technology	5	1.1594	0.849

Source: Study Data (2019)

Table 4.28 shows that the p values of the 10 univariate Ljung-Box tests Q tests were not statistically significant. Therefore, the study failed to reject all 10 null hypotheses of no autocorrelation of standardized residuals. Consequently, all 10 univariate GARCH (1,1) models with exogenous variance regressors that were utilized for the interaction equations were deemed to be correctly specified with apt goodness of fit.

4.8.3 Summary of Tests for Moderating Effect of Liquidity

Helm and Mark (2012) note that in order for a moderating effect to be deemed present, the coefficients of the interaction terms must be statistically significant. Table 4.29 summarizes the interaction terms, in terms of their statistical significance, at the 10% level.

Table 4.29: Significance of Interaction Terms

Sector	Interaction Terms	Interaction Term Statistically Significant?
Agricultural	$IT_{s1,t-1}$	Yes
	$IT_{v1,t-1}$	Yes
Automobiles & Accessories	$IT_{s2,t-1}$	Yes
	$IT_{v2,t-1}$	Yes
Banking	$IT_{s3,t-1}$	Yes
	$IT_{v3,t-1}$	No
Commercial & Services	$IT_{s4,t-1}$	Yes
	$IT_{v4,t-1}$	Yes
Construction & Allied	$IT_{s5,t-1}$	No
	$IT_{v5,t-1}$	No
Energy & Petroleum	$IT_{s6,t-1}$	Yes
	$IT_{v6,t-1}$	Yes
Insurance	$IT_{s7,t-1}$	Yes
	$IT_{v7,t-1}$	No
Investment	$IT_{s8,t-1}$	Yes
	$IT_{v8,t-1}$	No
Manufacturing & Allied	$IT_{s9,t-1}$	Yes
	$IT_{v9,t-1}$	No
Telecommunications & Technology	$IT_{s10,t-1}$	Yes
	$IT_{v10,t-1}$	No

Source: Study Data (2019)

As per Table 4.29, both interaction terms in the Agricultural, Automobiles & Accessories, Commercial & Services, and Energy & Petroleum sectors were statistically significant. Therefore, following the Helm and Mark (2012) criteria, it was concluded that there was a

moderating effect of liquidity on the relationship between the independent variables and the dependent variable in these sectors.

The study further considered the changes in the R^2 after fitting of the interaction models in order to evaluate whether there was an improvement in the ability of the regressors' variability to explain the dependent variable's variability after inclusion of the moderator and interacting terms. Aguinis (2004) notes that if there is any moderating effect present, the interaction model should have a higher coefficient of determination than the base model. Table 4.30 compares the changes in the R^2 after estimation of the interaction model.

Table 4.30: Change in R Squared after including the Moderating Variable and Interaction Terms

Sector	R Squared of Base Model	R Squared of Interaction Model	Change in R Squared
Agricultural	0.009708	0.01423	0.004522
Automobiles & Accessories	0.000167	0.00133	0.001159
Banking	0.023197	0.02135	-0.001847
Commercial & Services	0.015315	0.02053	0.005212
Construction & Allied	0.006603	0.00594	-0.000668
Energy & Petroleum	0.001119	0.00132	0.000201
Insurance	0.011356	0.01072	-0.000633
Investment	0.001708	0.00159	-0.000122
Manufacturing & Allied	0.001701	0.00057	-0.001133
Telecommunications & Technology	0.005547	0.00460	-0.000949

Source: Study Data (2019)

It can be noticed in Table 4.30 that for the Agricultural, Automobiles & Accessories, Commercial & Services, and Energy & Petroleum sectors, the R^2 of the respective interaction models was greater than that of the base models. Following Aguinis (2004), the conclusion is that liquidity has a significant moderation effect on the relationship between the independent variables and the dependent variable in these four sectors. Therefore, these results are in agreement with those presented in Table 4.29. A major communality of the sectors in which significant moderation effects of liquidity are extant is that they are all thinly traded sectors. This is deduced from the fact that the mean liquidity of these sectors is extremely low, relative to other NSE sectors (check descriptive statistics of liquidity in Table 4.3; section 4.2). These results are in coherence with Andrew and Jiang (2000) who note that boosting liquidity in thinly traded sectors provides a mechanism for dissipation of accumulated persistence of GARCH effects. Therefore, when liquidity of such sectors is improved, their shock and volatility transmission patterns become more manifest since these patterns are enhanced by increased activities of market players.

Xiao, Brooks, and Wong (2009) concur and add that in thinly traded sectors, an increment in liquidity deflates volatility persistence coefficients, implying that the speed of transmission of past shocks and volatilities is higher in more liquid markets. Fong and Wong (2006) posit that higher liquidity hastens the transmission speed of shocks and volatility in thinly traded sectors. This faster onset of the effects of shocks and persistence of volatility is actually beneficial: A quicker diffusion speed minimizes the turbulent intervening period, between impact of shocks and elevation of volatility, thereby enabling market participants to structure robust interventions against the oncoming surge in volatility.

Miyakoshi (2012) notes that asset values in illiquid sectors react to shocks discretely. This implies that since trading in such sectors is depressed, the few trading opportunities that are available are usually fraught with higher than normal volatility - especially in illiquid sectors that are reeling from the effects of a recent shock. Higher liquidity creates more trading opportunities thereby enabling prices to react to accrued shocks in a continuous manner. Likewise, Xu, Taylor and Lu (2018) posit that liquidity allows for market trends to be more manifest thereby enhancing forecasting procedures. This augments the reliability of volatility forecasting models. Table 4.31 summarizes the results of testing Hypothesis *v*

Table 4.31: Summary of Results of Testing Hypothesis *v*

Sector	Null Hypothesis	Decision
1	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 1 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
2	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 2 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
3	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 3 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**
4	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 4 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
5	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 5 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**
6	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 6 of the Nairobi Securities Exchange, Kenya.	**Reject H_0**
7	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 7 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**
8	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 8 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**
9	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 9 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**
10	There is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of sector 10 of the Nairobi Securities Exchange, Kenya.	**Do not Reject H_0**

Where:

1 is Agricultural Sector
2 is Automobiles & Accessories
3 is Banking Sector
4 is Commercial & Services Sector
5 is Construction & Allied Sector
6 is Energy & Petroleum Sector
7 is Insurance Sector
8 is Investment Sector
9 is Manufacturing & Allied Sector
10 Telecommunications & Technology

Source: Study Data (2019)

As per Table 4.31, the null hypothesis that *there is no moderating effect of liquidity on the relationship between own past shocks and own past volatility and volatility of each sector of the Nairobi Securities Exchange, Kenya* is rejected with respect to the Agricultural, Automobiles & Accessories, Commercial & Services, and Energy & Petroleum sectors. The implication is that in these four sectors, liquidity moderates the effect of own past shocks as well as that of own past volatility on the level of prevailing volatility as at any given time. Significant moderating effects of liquidity were not detected for the other six sectors.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS

5.1 Introduction

This chapter outlines the summary, conclusions, and policy implications of the study. Moreover, it also presents the study's limitations and suggestions for further research.

5.2 Summary of the Study

The Nairobi Securities Exchange plays a pivotal role in the local and regional economy. Being the largest securities exchange in East and Central Africa, its essence in provision of investment avenues and opportunities for portfolio diversification and raising of capital cannot be overemphasized. This importance notwithstanding, NSE market players have been operating without adequate guidance on the prevalence of volatility persistence in the NSE's sectors and knowledge on the transmission patterns of shocks and volatility in this market.

Using econometric tools, the study investigated how the level of sectoral volatility in the NSE in any given week is influenced by shocks from the previous week and level of volatility of the previous week, as well as how the level of sectoral liquidity in any week affects the transmission of own shocks and volatility. The causal research design was utilized to yield evidence on the existence and nature of temporal dependences between time series variables. In all models that were fitted, the regressors were taken at a single lag. The census approach was used to extract a sample of 10 sectors from the 13 NSE's sectors. These 10 sectors are the ones which met the criteria for inclusion in the sample. Thereafter, weekly time series data on the returns and liquidity of these 10 sectors, for the 13th June 2008 to 8th February 2019 period was utilized for empirical analysis.

A VAR(1)BEKK-MGARCH(1,1) model was used to undertake the analysis which was required to accomplish the study's first four objectives. Next, Univariate GARCH (1,1) models and univariate GARCH(1,1) models with exogenous variance regressors were used to generate the results for making inferences on the study's fifth objective.

The first objective of the study was to investigate the effect of own past shocks on volatility of returns in each sector of the Nairobi Securities Exchange, Kenya. The study found out that the volatility in all NSE sectors in any given week is influenced positively by their own shocks from the previous week. The implication is that shocks to all NSE sectors in any given week will lead to a surge in their respective volatilities in the following week.

The second objective was to evaluate the effect of cross past shocks on the volatility of returns in each sector of the Nairobi Securities Exchange, Kenya. Here, the study was interested in exploring the shock transmission patterns of the NSE sectors, i.e. how the volatility of each sector in a given week is influenced by shocks emanating from other sectors in the previous week. In this regard, the study found out that the volatilities of all NSE sectors are influenced by cross past shocks from at least one of the other sectors. Volatility of the Agricultural and Commercial & Services Sectors is influenced by the largest number of cross past shocks from other sectors (7), while the volatility of the Automobiles & Accessories Sector in any given week is least affected by cross shocks of other sectors from the previous week, since it reacts to the cross past shocks of only one other sector. In terms of the ability of a sector's shocks in one period to influence the volatility of other sectors, the Telecommunications & Technology and Investment Sectors were found to be most influential. Shocks that impact these two sectors in any given week have an influence on the volatility of 7 other sectors in the following week. Conversely, past shocks to the

Automobiles & Accessories Sector were found to be least consequential in terms of influencing the volatility of other sectors; they have a significant effect on the volatility of only two other sectors. In total, a total of 44 cross shock transmission relationships were found to be present within the 10 sampled sectors of the NSE.

The third objective of the study was to examine the effect of own past volatility on (current) volatility of returns in each sector of the Nairobi Securities Exchange, Kenya. Here, the study was keen on investigating the presence and magnitude of persistence of own volatility in the NSE's sectors. The study found out that in the Automobiles & Accessories, Commercial & Services, Construction & Allied, and Energy & Petroleum Sectors, the volatility for any given week is not influenced significantly by their respective volatilities of the previous week. For these four sectors, volatility can therefore be deemed to have a short term memory since the impact of shocks dies off rather fast, and it is not reflected via the persistence of volatility. Conversely, for the Agricultural, Banking, Insurance, Investment, Manufacturing & Allied, and Telecommunications & Technology sectors, there is a significant relationship between the level of volatility in each of these sectors for any given week and the its level for the preceding week. The Agricultural sector has the highest level of persistence of own volatility. In this sector, the rate at which own volatility decays is very low and an almost perfect autocorrelation exists between the magnitude of volatility witnessed in this sector in any given week and the immediate next week. On the contrary, the Investment sector was found to have the least level of persistence of own volatility.

The study's fourth objective was to establish the effect of cross past volatilities on the (current) volatility of returns in each sector of the Nairobi Securities Exchange, Kenya. The key issue of interest was to map the NSE sectors which had significant volatility transmission

linkages. All sectors were found to have volatility transmission linkages, but with different intensities. Volatilities of the Banking and Manufacturing & Allied sectors have the largest tendency to influence the level of volatility in other sectors, since they spill over to influence the volatility of six other sectors. On the other hand, volatility of the Telecommunications & Technology Sector has the least tendency to affect next-period volatility of other sectors, since it has only one such linkage. The study also found out that the Commercial & Services sector is very vulnerable to contagion flows: Volatility of this sector in any given week tends to react to the previous week's volatility of all other sectors of the NSE, except the Telecommunications & Technology Sector. Additionally, the Telecommunications & Technology Sector was found to be the most robust sector, in terms of withstanding the influence of cross volatility from other sectors. Its volatility is affected by contagion flows from only the Insurance sector.

The study's fifth objective was to appraise the moderating effect of liquidity on the relationship between own past shocks & own past volatility and volatility of returns in each sector of the Nairobi Securities Exchange, Kenya. The study found liquidity to have a significant moderating effect on the relationship between own past shocks & own past volatility and current volatility in only the Agricultural, Banking, Commercial & Services, and Energy & Petroleum sectors of the NSE. For these four sectors, the strength of the influence of own past shocks and volatility on current volatility depends on the prevailing level of liquidity.

Generally, it can be noticed that volatility of the NSE's sectors in any given week is more responsive to own shocks from the previous week as compared to own volatility of the previous week. In all 10 sectors, own past shocks had a significant effect on current volatility.

Conversely, persistence of own volatility was found to be significant in only 6 NSE sectors. Even with respect to the cross influences, cross past shocks have a larger influence on current volatility than cross past volatilities, from a standpoint of the entire market: Amongst to 10 NSE sectors, 44 cross shock transmission relationships were statistically significant but only 40 cross volatility transmission relationships were statistically significant.

5.3 Conclusions

The study concludes that own shock transmission effects are present in each sector of the NSE. Own shock transmission effects are strongest in the Automobiles and Accessories Sector and are weakest in the Telecommunications and Technology sector. Therefore, if the returns of any NSE sector are impacted by a shock in a given week, there will be a significant consequential elevation in own sectoral volatility in the following week as a response to the shock.

Moreover, the study concludes that the volatility of each NSE sectors in any given week is responsive, albeit at varying intensities, to shocks that impacted other sectors in the previous week. It is deduced that the volatility of the Agricultural sector is most responsive to shocks from other sectors, since it is affected significantly by lagged shocks of seven other NSE sectors. Additionally, the study concludes that the Automobiles & Accessories Sector has the highest level of resilience, in terms of withstanding the effect of shocks from other sectors. This is because its volatility, in any given week, is affected significantly by previous-week shocks of only one other sector. The study further concludes that shocks to the Investment and Telecommunications & Technology sectors in any given week have the highest influence on the volatility of other sectors. Shocks to these two sectors in any given week have a significant effect on the volatility of seven other sectors in the following week. Other the

other hand, the Automobiles & Accessories sector is concluded to be least effectual in this respect, since its shocks in a given week have a significant influence on the volatility of only two other sectors in the following week.

On persistence of own volatility, the study concludes that own volatility is persistent in the Agricultural, Banking, Insurance, Investment, Manufacturing & Allied, and Telecommunications & Technology Sector. In these six sectors, there is a statistically significant link between their respective levels of volatility in any given week and their corresponding levels of volatility in the following week. Therefore, the level of volatility for these six sectors in any given week is partly influenced by its level in the previous week. On the other hand, there is no significant relationship between the level of volatility in any given week *vis a vis* that of the succeeding week for the Automobiles & Accessories, Commercial & Services, Construction & Allied, and Energy & Petroleum Sectors.

On cross-sector volatility transmission, the study concludes that in each NSE sector, the level of volatility in each week is partly dependent on the volatility that was prevailing in other NSE sectors in the previous week. Although all sectors are affected by contagion flows, the strength of this phenomenon isn't uniform for all sectors: The study concludes that the Banking and Manufacturing & Allied sectors are most influential in perpetuating contagion flows. This is because the level of volatility for a total of six NSE sectors in any given week is dependent of the level of these two sectors' volatility in the previous week. On the other hand, the volatility of the Telecommunications & Technology Sector has the least tendency to affect next-period volatility of other sectors, since it has only one such linkage. Moreover, the study concludes that the Commercial & Services sector has the highest level of vulnerability to contagion flows. Its volatility in any given week is reactive to the previous-week volatility

of all other eight sectors of the NSE, except the Telecommunications & Technology Sector. On the other hand, it is concluded that the Telecommunications & Technology Sector is most robust, in terms of withstanding the influence of cross volatility from other sectors. Its volatility is affected by contagion flows from only the Insurance sector.

With respect to the moderating effect of liquidity, the study concludes that liquidity has a moderating effect on the transmission of own shocks and volatility in the Agricultural, Automobiles & Accessories, Commercial & Services, and Energy & Petroleum sectors. Therefore, in these four sectors, the level of sectoral liquidity in any given week has an effect on the strength of the relationship between own shocks and volatility in this week and the volatility of the following week. Conversely, for the Banking, Construction & Allied, Insurance, Investment, Manufacturing & Allied, and Telecommunications & Technology sectors, sectoral liquidity does not affect the strength or significance of the relationship between own shocks and volatility in any given week and the volatility of the following week.

Lastly, it can be generally concluded that sectoral volatility in the NSE at any given time is more influenced by recent shocks (both own and cross) than by the persistence of previous periods' volatility (both own and cross). The study found out that in all 10 sectors, volatility in any week is influenced by own shocks from the previous week. However, significant persistence of own volatility was detected in only 6 sectors. Moreover, there are 44 cross shock transmission linkages that were detected in the NSE sectors but only 40 cross volatility spillover relationships.

5.4 Contribution to Knowledge

The main contribution of this study is that it deeply delves into an under researched area. Hitherto this study, there was scanty evidence in the literature on the extant relationship between the level of sectoral volatility, as at any given moment in time, and its level in the previous period. Furthermore, the study also addresses the gap in the literature pertaining the effect of previous-period shocks on the level of sectoral volatility as at any given time.

Secondly, in addition to investigating direct transmission linkages of sectoral shocks and volatility, the study examines cross transmission linkages of sectoral shocks and volatility. This brings out a fuller picture of the complex influences of past shocks and volatilities on the volatility of each NSE sector. In so doing, the study augments the literature with empirical evidence on the temporal interrelationships of the NSE's sectors' second order moments.

Thirdly, the study utilizes a market-wide approach and thus evaluates the shock and volatility transmission linkages of all NSE sectors. This is in contrast with previous studies that investigated the shock and volatility transmission linkages of only a few sectors of NSE. In so doing, this study depicts a holistic picture on the subject of shock and volatility transmission in the entire market, and hence it has a higher scope of influence *vis-à-vis* the limited studies.

Finally, the study explores the moderating influence of sectoral liquidity on the speed on transmission of own shocks and volatilities. It contributes to the literature by establishing that in some NSE sectors, sectoral liquidity has a moderating effect on the transmission of own shocks and volatilities, while in others, the moderating effect of sectoral liquidity is nonexistent.

5.5 Policy Implications

The study found out that a shock to each market sector in any given week will directly influence its volatility in the following week. Moreover, the elevated volatility might become persistent and continue to influence the level of volatility in more future weeks; but only in the six sectors where own volatility is persistent. Therefore, the study recommends that once a shock to any sector is detected, investors and portfolio managers should prepare for an elevation of the idiosyncratic volatility in the near future and undertake apt mitigation measures; which might include disposing affected stocks, to protect their portfolios from excessive volatility. The study further recommends that the Capital Markets Authority should monitor markets proactively and be ready to enforce administrative measures, such as trading curbs, to prevent the speculative gains and dramatic losses that lead to a spike in volatility immediately after the impact of a major shock.

The study also finds out that the volatility of each sector's returns in any given week is influenced by the shocks that impacted other sectors in the previous week, ostensibly due to inter - sector linkages. However, the scale of this effect is not uniform for all sectors: Some sectors are more susceptible to influences of cross lagged shocks, as compared to their peers. In view of these results, the study recommends that portfolio managers and investors should choose the sectors to invest in on the basis of their respective asset allocation strategies and the findings of this study. For instance, conservative investors should ensure that they do not include stocks from many sectors that have been proven to have shock transmission linkages, since this can lead to an elevation in overall portfolio volatility. On the other hand, aggressive investors might even ignore magnanimous shock transmission linkages in portfolio selection; as long as they are able to create a portfolio with good prospects of huge returns.

Since the study found out that there is no persistence of own lagged volatility in four market sectors; it recommends that investors with a low tolerance for long term volatility should focus on stocks listed under these sectors. These could include speculative short term investors and conservative investors. On the other hand, growth investors can focus on stocks listed under the six sectors with volatility persistence, since their investment horizon is long and intermediate volatility isn't much of a concern to them. Moreover, aggressive investors should also focus on these six sectors due to their upside: the prospects of higher returns, vis-à-vis their less volatile peers.

The study found out that all sectors have cross volatility transmission linkages, but at varying levels of intensity. Therefore, it recommends that investors and other market participants should aim to manage overall portfolio risk by minimizing the risk of financial contagion. This problem could arise if several stocks from sectors that have volatility transmission linkages are included in the same portfolio. Additionally, they can use the results of this study to obtain one period forecasts of volatility and proactively implement remedial measures in case there is forecasted excess volatility. Such measures could include volatility targeting - a strategy that entails dynamic rebalancing of portfolio composition in order to attain a constant level of volatility over a given future time horizon.

Additionally, the study recommends that the market regulators (Central Bank of Kenya and Capital Markets Authority) and the NSE management should actively monitor the tendency of sectors' volatility to affect other sectors' volatility. This way, they can predict the effect of volatility in a particular sector on next period volatilities of other sectors and undertake preemptive measures to forestall the undesirable effects of cross-sector transmission of volatility. Feasible preemptive measures could include adjustment of macroeconomic

indicators (such as lowering of interest rates or increasing foreign currency supply) and implementation of administrative actions (such as imposing of trading restrictions in certain sectors).

Finally, since the study found out that liquidity moderates the transmission of own shocks and own volatility in four NSE sectors, it is recommended that volatility management practices in portfolios that include stocks from these four sectors should be robust enough to take into account the effect of liquidity on the transmission of own shocks and volatilities.

5.6 Limitations and Recommendations for Further Research

Survivorship bias was contemplated in this study as a major limitation. Since the study was based on firms that traded consistently over the data collection period, firms that were dormant, had not been listed at the start of the data collection period, or were delisted before the end of the data collection period were excluded from the study. Due to the fact that results of this study are based on data from only the firms that were included in the sample, there is likely to be a differential between the estimated output and the real situation in the market. Nevertheless, the level of survivorship bias is likely to be minimal since the stocks which account for the bulk majority of variability in the respective sectors were traded consistently over the data collection period and hence their data was taken into account.

The fact that weekly data was utilized for empirical analysis meant that effects which would have been captured if the research was based on higher frequency data (such as daily data) or lower frequency data (such as monthly data) were missed. However, from the review of literature, it was apparent that weekly data has the optimal frequency for empirical investigations. Bearing in mind the fact that the study had a horizon that spanned more than

10 years, daily data was deemed to be too noisy while monthly data had an inadequate number of time dimension observations.

Just like all empirical models have limitations, the GARCH models that were utilized in this study have some drawbacks. The main disadvantage is that these models assume that positive and negative shocks have the same effects on volatility. In practice, it is well known that stock prices responds differently to positive and negative shocks. Negative shocks lead to higher volatility than positive shocks of the same magnitude. Moreover, all empirical models of this study utilized only a single lag thereby ignoring the effects that could have been accounted for if the number of lags was higher. However, the limitations notwithstanding, the literature (Bauwens *et al*, 2006) posits that first order GARCH models have the highest power, as far as modelling of volatility dynamics is concerned. Moreover, the lag order of one was chosen on the basis of precedence from the literature or statistical information criteria and thus its optimality is assured.

The study proposes some feasible suggestions which can be undertaken for further research to augment its findings:

Firstly, one can consider utilizing high frequency data over a shorter time span to evaluate the pertinent temporal dynamics of such data, such as the day of week effects and hour of the day effects, in addition to the shock and volatility transmission effects that are existent in short time spans.

Secondly, future research can delve into the confluence of market volatility and macroeconomic variables by investigating how different indicators, such as interest rates, inflation rates, and exchange rates affect and/or are affected by sectoral volatility. This can provide a more effectual basis for making policy recommendations.

Thirdly, one can contemplate to expand the scope of the study and investigate the shock and volatility transmission linkages that exist between the NSE and other regional stock exchanges, such as the USE and the DSE, and their effect on regional capital markets.

Finally, future research can explore the shock and volatility transmission trends that are existent between different types of NSE listed firms, without regard to the sectors that they are listed in. This can help in unveiling the dynamics of shock and volatility flows from different dimensions. For instance, such effects might be investigated between the small capitalization versus the large capitalization firms, financial versus non-financial firms, or mature firms versus growth firms.

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APPENDICES

Appendix I: Sectors of the NSE and their Constituent Firms

Sector	Firms	No. of Firms
AGRICULTURAL	Eaagads Ltd	7
	Kapchorua Tea Co. Ltd	
	Kakuzi Ltd	
	Limuru Tea Co. Ltd	
	Rea Vipingo Plantations Ltd	
	Sasini Ltd	
	Williamson Tea Kenya Ltd	
AUTOMOBILES & ACCESSORIES	Car and General (K) Ltd	1
BANKING	Barclays Bank Ltd	12
	Stanbic Holdings Ltd	
	I&M Holdings Ltd	
	Diamond Trust Bank Kenya Ltd	
	HF Group Ltd	
	KCB Group Ltd	
	National Bank of Kenya Ltd	
	NIC Group Plc	
	Standard Chartered Bank Ltd	
	Equity Group Holdings	
	The Co-operative Bank of Kenya Ltd	
	BK Group PLC	
COMMERCIAL & SERVICES	Express Ltd	12
	Sameer Africa PLC	
	Kenya Airways Ltd	
	Nation Media Group	
	Standard Group Ltd	
	TPS Eastern Africa (Serena) Ltd	
	Scangroup Ltd	
	Uchumi Supermarket Ltd	
	Longhorn Publishers Ltd	
	Atlas Development and Support Services	
	Deacons (East Africa) Plc	
	Nairobi Business Ventures Ltd	
CONSTRUCTION & ALLIED	Athi River Mining	5
	Bamburi Cement Ltd	
	Crown Berger Ltd	

	E.A.Cables Ltd	
	E.A.Portland Cement Ltd	
ENERGY & PETROLEUM	KenolKobil Ltd	5
	Total Kenya Ltd	
	KenGen Ltd	
	Kenya Power & Lighting Co Ltd	
	Umeme Ltd	
INSURANCE	Jubilee Holdings Ltd	6
	Sanlam Kenya PLC	
	Kenya Re-Insurance Corporation Ltd	
	Liberty Kenya Holdings Ltd	
	Britam Holdings Ltd	
	CIC Insurance Group Ltd	
INVESTMENT	Olympia Capital Holdings ltd	5
	Centum Investment Co Ltd	
	Trans-Century Ltd	
	Home Afrika Ltd	
	Kurwitu Ventures	
INVESTMENT SERVICES	Nairobi Securities Exchange Ltd	1
MANUFACTURING & ALLIED	B.O.C Kenya Ltd	9
	British American Tobacco Kenya Ltd	
	Carbacid Investments Ltd	
	East African Breweries Ltd	
	Mumias Sugar Co. Ltd	
	Unga Group Ltd	
	Eveready East Africa Ltd	
	Kenya Orchards Ltd	
	Flame Tree Group Holdings Ltd	
TELECOMMUNICATION AND TECHNOLOGY	Safaricom Ltd	1
REAL ESTATE INVESTMENT TRUST	Stanlib Fahari I-REIT	1
EXCHANGE TRADED FUND	New Gold Issuer (RP) Ltd	1

Source: Nairobi Securities Exchange (2019*)*

Appendix II: Sectors of the NSE that Were Included in the Sample and their Constituent Firms

Sector	Firms	No. of Firms
AGRICULTURAL	Eaagads Ltd	6
	Kapchorua Tea Co. Ltd	
	Kakuzi Ltd	
	Limuru Tea Co. Ltd	
	Sasini Ltd	
	Williamson Tea Kenya Ltd	
AUTOMOBILES & ACCESSORIES	Car and General (K) Ltd	1
BANKING	Barclays Bank Ltd	9
	Stanbic Holdings Ltd	
	Diamond Trust Bank Kenya Ltd	
	HF Group Ltd	
	KCB Group Ltd	
	National Bank of Kenya Ltd	
	NIC Group Plc	
	Standard Chartered Bank Ltd	
	Equity Group Holdings	
COMMERCIAL & SERVICES	Express Ltd	8
	Sameer Africa PLC	
	Kenya Airways Ltd	
	Nation Media Group	
	Standard Group Ltd	
	TPS Eastern Africa (Serena) Ltd	
	Scangroup Ltd	
	Uchumi Supermarket Ltd	
CONSTRUCTION & ALLIED	Athi River Mining	5
	Bamburi Cement Ltd	
	Crown Berger Ltd	
	E.A.Cables Ltd	
	E.A.Portland Cement Ltd	
ENERGY & PETROLEUM	Total Kenya Ltd	3
	KenGen Ltd	
	Kenya Power & Lighting Co Ltd	
INSURANCE	Jubilee Holdings Ltd	3
	Sanlam Kenya PLC	
	Kenya Re-Insurance Corporation Ltd	
INVESTMENT	Olympia Capital Holdings ltd	2
	Centum Investment Co Ltd	
MANUFACTURING & ALLIED	B.O.C Kenya Ltd	7

	British American Tobacco Kenya Ltd	
	Carbacid Investments Ltd	
	East African Breweries Ltd	
	Mumias Sugar Co. Ltd	
	Unga Group Ltd	
	Kenya Orchards Ltd	
TELECOMMUNICATION & TECHNOLOGY	Safaricom Ltd	1

Source: Researcher (2019*)*

Appendix III: Approval of Research Proposal

KENYATTA UNIVERSITY
GRADUATE SCHOOL

E-mail: dean-graduate@ku.ac.ke
Website: www.ku.ac.ke

P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 810901 Ext. 57530

Internal Memo

FROM: Dean, Graduate School

DATE: 7th March, 2019

TO: Mr. Gabriel L. Munene
C/o Accounting & Finance Dept.
Kenyatta University

REF: D86/CTY/22951/12

SUBJECT: APPROVAL OF RESEARCH PROPOSAL

This is to inform you that Graduate School Board at its meeting of 6th March, 2019 approved your Research Proposal for the Ph.D. Degree, entitled "Lagged Disturbance and Volatility in the Nairobi Securities Exchange, Kenya".

You may now proceed with your Data collection, subject to clearance with the National Commission for Science Technology, & Innovation

As you embark on your data collection, please note that you will be required to submit to Graduate School completed supervision Tracking Forms per semester. The form has been developed to replace the progress Report Forms. The Supervision Tracking Forms are available at the University's Website under Graduate School webpage downloads.

By copy of this letter, the Registrar (Academic) is hereby requested to grant you substantive registration for your Ph.D. studies.

Thank you.

REUBEN MURIUKI
FOR: DEAN, GRADUATE SCHOOL

c.c. Registrar (Academic) Att. Mr. Likam
Chairman, Accounting & Finance Department

Supervisors:

1. Dr. Eddie Simiyu
   C/o Accounting & Finance Dept.
   KENYATTA UNIVERSITY
2. Dr. Julius Korir
   C/o Accounting & Finance Dept.
   KENYATTA UNIVERSITY

RM/cao

Appendix IV(a): Document Review Guide I: Data Entry Sheet 1

		Time ID	**1**	**2**	**3**				**554**	**555**
NSE SECTORS	**LISTED FIRMS**	**End Week Date**	Friday, June 6, 2008	Friday, June 13, 2008	Friday, June 20, 2008	.	.	.	Friday, February 1, 2019	Friday, February 8, 2019
		(All values are in KES)								
AGRICULTURAL	Eaagads Ltd	Share Price								
		Market Capitalization								
	Kapchorua Tea Co. Ltd	Share Price								
		Market Capitalization								
	Kakuzi Ltd	Share Price								
		Market Capitalization								
	Limuru Tea Co. Ltd	Share Price								
		Market Capitalization								
	Sasini Ltd	Share Price								
		Market Capitalization								
	Williamson Tea Kenya Ltd	Share Price								
		Market Capitalization								
AUTOMOBILES & ACCESSORIES	Car and General (K) Ltd	Share Price								
		Market Capitalization								
BANKING	Barclays Bank Ltd	Share Price								
		Market Capitalization								
	Stanbic Holdings Ltd	Share Price								
		Market Capitalization								
	Diamond Trust Bank Kenya Ltd	Share Price								
		Market Capitalization								

	HF Group Ltd	Share Price								
		Market Capitalization								
	KCB Group Ltd	Share Price								
		Market Capitalization								
	National Bank of Kenya Ltd	Share Price								
		Market Capitalization								
	NIC Group Plc	Share Price								
		Market Capitalization								
	Standard Chartered Bank Ltd	Share Price								
		Market Capitalization								
	Equity Group Holdings	Share Price								
		Market Capitalization								
COMMERCIAL & SERVICES	Express Ltd	Share Price								
		Market Capitalization								
	Sameer Africa PLC	Share Price								
		Market Capitalization								
	Kenya Airways Ltd	Share Price								
		Market Capitalization								
	Nation Media Group	Share Price								
		Market Capitalization								
	Standard Group Ltd	Share Price								
		Market Capitalization								
	TPS Eastern Africa (Serena) Ltd	Share Price								
		Market Capitalization								
	Scangroup Ltd	Share Price								
		Market Capitalization								
	Uchumi Supermarket Ltd	Share Price								
		Market Capitalization								

CONSTRUCTION & ALLIED	Athi River Mining	Share Price								
		Market Capitalization								
	Bamburi Cement Ltd	Share Price								
		Market Capitalization								
	Crown Berger Ltd	Share Price								
		Market Capitalization								
	E.A.Cables Ltd	Share Price								
		Market Capitalization								
	E.A.Portland Cement Ltd	Share Price								
		Market Capitalization								
ENERGY & PETROLEUM	Total Kenya Ltd	Share Price								
		Market Capitalization								
	KenGen Ltd	Share Price								
		Market Capitalization								
	Kenya Power & Lighting Co Ltd	Share Price								
		Market Capitalization								
INSURANCE	Jubilee Holdings Ltd	Share Price								
		Market Capitalization								
	Sanlam Kenya PLC	Share Price								
		Market Capitalization								
	Kenya Re-Insurance Corporation Ltd	Share Price								
		Market Capitalization								
INVESTMENT	Olympia Capital Holdings ltd	Share Price								
		Market Capitalization								
	Centum Investment Co Ltd	Share Price								
		Market Capitalization								

MANUFACTURING & ALLIED	B.O.C Kenya Ltd	Share Price								
		Market Capitalization								
	British American Tobacco Kenya Ltd	Share Price								
		Market Capitalization								
	Carbacid Investments Ltd	Share Price								
		Market Capitalization								
	East African Breweries Ltd	Share Price								
		Market Capitalization								
	Mumias Sugar Co. Ltd	Share Price								
		Market Capitalization								
	Unga Group Ltd	Share Price								
		Market Capitalization								
	Kenya Orchards Ltd	Share Price								
		Market Capitalization								
TELECOMMUNICATION AND TECHNOLOGY	Safaricom Ltd	Share Price								
		Market Capitalization								

Source: Researcher (2019*)*

Appendix IV(b): Document Review Guide II: Data Entry Sheet 2

		Time ID	**1**	**2**	**3**				**2676**	**2677**
NSE SECTORS	**LISTED FIRMS**	**End Week Date**	Friday, June 6, 2008	Monday, June 9, 2008	Tuesday, June 10, 2008	.	.	.	Thursday, February 7, 2019	Friday, February 8, 2019
		(All values are in KES)								
AGRICULTURAL	Eaagads Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kapchorua Tea Co. Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kakuzi Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Limuru Tea Co. Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Sasini Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Williamson Tea Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

AUTOMOBILES & ACCESSORIES	Car and General (K) Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
BANKING	Barclays Bank Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Stanbic Holdings Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Diamond Trust Bank Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	HF Group Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	KCB Group Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	National Bank of Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

	NIC Group Plc	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Standard Chartered Bank Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Equity Group Holdings	Total Number of Shares Traded								
		Total Number of Tradable Shares								
COMMERCIAL & SERVICES	Express Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Sameer Africa PLC	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kenya Airways Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Nation Media Group	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Standard Group Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

	TPS Eastern Africa (Serena) Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Scangroup Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Uchumi Supermarket Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
CONSTRUCTION & ALLIED	Athi River Mining	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Bamburi Cement Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Crown Berger Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	E.A.Cables Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	E.A.Portland Cement Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

ENERGY & PETROLEUM	Total Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	KenGen Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kenya Power & Lighting Co Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
INSURANCE	Jubilee Holdings Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Sanlam Kenya PLC	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kenya Re-Insurance Corporation Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
INVESTMENT	Olympia Capital Holdings ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Centum Investment Co Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

MANUFACTURING & ALLIED	B.O.C Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	British American Tobacco Kenya Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Carbacid Investments Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	East African Breweries Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Mumias Sugar Co. Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Unga Group Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								
	Kenya Orchards Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

TELECOMMUNICATION AND TECHNOLOGY	Safaricom Ltd	Total Number of Shares Traded								
		Total Number of Tradable Shares								

Source: Researcher (2019*)*

Appendix V(a): Document Review Guide III: Data Abstraction Tool for Sectoral Returns

Time Series	Measurement	Formula	Data	Source: NSE Market Data (June 2008 - Feb 2019)
Returns of sector *1* in week *t*	Capital gain yield for sector *1*'s index in week *t*	Formula and data for value of sector *1*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{1,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *1* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *1* on the last trading day of each week *t*	
		Formula and data for return of sector *1* in week *t*		
		$R_{1,t} = \frac{(\psi_{1,t} - \psi_{1,t-1})}{\psi_{1,t-1}}$	▪ value of sector *1*'s index for week *t* ▪ value of sector *1*'s index for week *t-1*	
Returns of sector *2* in week *t*	Capital gain yield for sector *2*'s index in week *t*	Formula and data for value of sector *2*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{2,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *2* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *2* on the last trading day of each week *t*	
		Formula and data for return of sector *2* in week *t*		
		$R_{2,t} = \frac{(\psi_{2,t} - \psi_{2,t-1})}{\psi_{2,t-1}}$	▪ value of sector *2*'s index for week *t* ▪ value of sector *2*'s index for week *t-1*	
Returns of sector *3* in week *t*	Capital gain yield for sector *3*'s index in week *t*	Formula and data for value of sector *3*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{3,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *3* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *3* on the last trading day of each week *t*	
		Formula and data for return of sector *3* in week *t*		
		$R_{3,t} = \frac{(\psi_{3,t} - \psi_{3,t-1})}{\psi_{3,t-1}}$	▪ value of sector *3*'s index for week *t* ▪ value of sector *3*'s index for week *t-1*	

<table>
<tr><td rowspan="4">Returns of sector 4 in week t</td><td rowspan="4">Capital gain yield for sector 4's index in week t</td><td colspan="2">Formula and data for value of sector 4's index for week t</td><td rowspan="4">Trading reports for the last trading day of each week</td></tr>
<tr><td>$\psi_{4,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$</td><td>▪ Prices of all stocks listed under sector 4 on the last trading day of each week t
▪ Capitalization of all stocks listed under sector 4 on the last trading day of each week t</td></tr>
<tr><td colspan="2">Formula and data for return of sector 4 in week t</td></tr>
<tr><td>$R_{4,t} = \frac{(\psi_{4,t} - \psi_{4,t-1})}{\psi_{4,t-1}}$</td><td>▪ value of sector 4's index for week t
▪ value of sector 4's index for week t-1</td></tr>
<tr><td rowspan="4">Returns of sector 5 in week t</td><td rowspan="4">Capital gain yield for sector 5's index in week t</td><td colspan="2">Formula and data for value of sector 5's index for week t</td><td rowspan="4">Trading reports for the last trading day of each week</td></tr>
<tr><td>$\psi_{5,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$</td><td>▪ Prices of all stocks listed under sector 5 on the last trading day of each week t
▪ Capitalization of all stocks listed under sector 5 on the last trading day of each week t</td></tr>
<tr><td colspan="2">Formula and data for return of sector 5 in week t</td></tr>
<tr><td>$R_{5,t} = \frac{(\psi_{5,t} - \psi_{5,t-1})}{\psi_{5,t-1}}$</td><td>▪ value of sector 5's index for week t
▪ value of sector 5's index for week t-1</td></tr>
<tr><td rowspan="4">Returns of sector 6 in week t</td><td rowspan="4">Capital gain yield for sector 6's index in week t</td><td colspan="2">Formula and data for value of sector 6's index for week t</td><td rowspan="4">Trading reports for the last trading day of each week</td></tr>
<tr><td>$\psi_{6,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$</td><td>▪ Prices of all stocks listed under sector 6 on the last trading day of each week t
▪ Capitalization of all stocks listed under sector 6 on the last trading day of each week t</td></tr>
<tr><td colspan="2">Formula and data for return of sector 6 in week t</td></tr>
<tr><td>$R_{6,t} = \frac{(\psi_{6,t} - \psi_{6,t-1})}{\psi_{6,t-1}}$</td><td>▪ value of sector 6's index for week t
▪ value of sector 6's index for week t-1</td></tr>
<tr><td rowspan="2">Returns of sector 7 in week t</td><td rowspan="2">Capital gain yield for sector 7's index in week t</td><td colspan="2">Formula and data for value of sector 7's index for week t</td><td rowspan="2">Trading reports for the last trading day of each week</td></tr>
<tr><td>$\psi_{7,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$</td><td>▪ Prices of all stocks listed under sector 7 on the last trading day of each week t
▪ Capitalization of all stocks listed under sector 7 on the last trading day of each week t</td></tr>
</table>

		Formula and data for return of sector *7* in week *t*		
		$R_{7,t} = \frac{(\psi_{7,t} - \psi_{7,t-1})}{\psi_{7,t-1}}$	▪ value of sector *7*'s index for week *t* ▪ value of sector *7*'s index for week *t-1*	
Returns of sector *8* in week *t*	Capital gain yield for sector *8*'s index in week *t*	Formula and data for value of sector *8*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{8,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *8* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *8* on the last trading day of each week *t*	
		Formula and data for return of sector *8* in week *t*		
		$R_{8,t} = \frac{(\psi_{8,t} - \psi_{8,t-1})}{\psi_{8,t-1}}$	▪ value of sector *8*'s index for week *t* ▪ value of sector *8*'s index for week *t-1*	
Returns of sector *9* in week *t*	Capital gain yield for sector *9*'s index in week *t*	Formula and data for value of sector *9*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{9,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *9* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *9* on the last trading day of each week *t*	
		Formula and data for return of sector *9* in week *t*		
		$R_{9,t} = \frac{(\psi_{9,t} - \psi_{9,t-1})}{\psi_{9,t-1}}$	▪ value of sector *9*'s index for week *t* ▪ value of sector *9*'s index for week *t-1*	
Returns of sector *10* in week *t*	Capital gain yield for sector *10*'s index in week *t*	Formula and data for value of sector *10*'s index for week *t*		Trading reports for the last trading day of each week
		$\psi_{10,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}}$	▪ Prices of all stocks listed under sector *10* on the last trading day of each week *t* ▪ Capitalization of all stocks listed under sector *10* on the last trading day of each week *t*	
		Formula and data for return of sector *10* in week *t*		
		$R_{10,t} = \frac{(\psi_{10,t} - \psi_{10,t-1})}{\psi_{10,t-1}}$	▪ value of sector *10*'s index for week *t* ▪ value of sector *10*'s index for week *t-1*	

Where:

Sector 1 is Agricultural Sector	Sector 6 is Energy & Petroleum Sector
Sector 2 is Automobiles & Accessories Sector	Sector 7 is Insurance Sector
Sector 3 is Banking Sector	Sector 8 is Investment Sector
Sector 4 is Commercial & Services Sector	Sector 9 is Manufacturing & Allied Sector
Sector 5 is Construction & Allied Sector	Sector 10 is Telecommunications & Technology Sector

Source: Researcher (2019*)*

Appendix V(b): Document Review Guide IV: Data Abstraction Tool for Sectoral Liquidity

Time Series	Measurement	Formula	Data	Source: NSE Market Data (June 2008 - Feb 2019)
Liquidity of Sector *1* in week *t*	Aggregate weekly stock turnover ratio for sector *1* in week *t*	$\omega_{1,t} = \frac{\sum_{d=1}^{5} \tau_{1d,t}}{\eta_{1,t}}$	▪ Number of Shares Traded of all stocks listed under sector *1* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *1* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *2* in week *t*	Aggregate weekly stock turnover ratio for sector *2* in week *t*	$\omega_{2,t} = \frac{\sum_{d=1}^{5} \tau_{2d,t}}{\eta_{2,t}}$	▪ Number of Shares Traded of all stocks listed under sector *2* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *2* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *3* in week *t*	Aggregate weekly stock turnover ratio for sector *3* in week *t*	$\omega_{3,t} = \frac{\sum_{d=1}^{5} \tau_{3d,t}}{\eta_{3,t}}$	▪ Number of Shares Traded of all stocks listed under sector *3* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *3* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *4* in week *t*	Aggregate weekly stock turnover ratio for sector *4* in week *t*	$\omega_{4,t} = \frac{\sum_{d=1}^{5} \tau_{4d,t}}{\eta_{4,t}}$	▪ Number of Shares Traded of all stocks listed under sector *4* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *4* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *5* in week *t*	Aggregate weekly stock turnover ratio for sector *5* in week *t*	$\omega_{5,t} = \frac{\sum_{d=1}^{5} \tau_{5d,t}}{\eta_{5,t}}$	▪ Number of Shares Traded of all stocks listed under sector *5* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *5* for each trading day of each week	Trading reports for each trading day of each week

Liquidity of Sector *6* in week *t*	Aggregate weekly stock turnover ratio for sector *6* in week *t*	$\omega_{6,t} = \frac{\sum_{d=1}^{5} \tau_{6d,t}}{\eta_{6,t}}$	▪ Number of Shares Traded of all stocks listed under sector *6* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *6* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *7* in week *t*	Aggregate weekly stock turnover ratio for sector *7* in week *t*	$\omega_{7,t} = \frac{\sum_{d=1}^{5} \tau_{7d,t}}{\eta_{7,t}}$	▪ Number of Shares Traded of all stocks listed under sector *7* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *7* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *8* in week *t*	Aggregate weekly stock turnover ratio for sector *8* in week *t*	$\omega_{8,t} = \frac{\sum_{d=1}^{5} \tau_{8d,t}}{\eta_{8,t}}$	▪ Number of Shares Traded of all stocks listed under sector *8* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *8* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *9* in week *t*	Aggregate weekly stock turnover ratio for sector *9* in week *t*	$\omega_{9,t} = \frac{\sum_{d=1}^{5} \tau_{9d,t}}{\eta_{9,t}}$	▪ Number of Shares Traded of all stocks listed under sector *9* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *9* for each trading day of each week	Trading reports for each trading day of each week
Liquidity of Sector *10* in week *t*	Aggregate weekly stock turnover ratio for sector *10* in week *t*	$\omega_{10,t} = \frac{\sum_{d=1}^{5} \tau_{10d,t}}{\eta_{10,t}}$	▪ Number of Shares Traded of all stocks listed under sector *10* for each trading day of each week ▪ Number of Tradable Shares of all stocks listed under sector *10* for each trading day of each week	Trading reports for each trading day of each week

Where:

Sector 1 is Agricultural Sector
Sector 2 is Automobiles & Accessories Sector
Sector 3 is Banking Sector
Sector 4 is Commercial & Services Sector
Sector 5 is Construction & Allied Sector
Sector 6 is Energy & Petroleum Sector
Sector 7 is Insurance Sector
Sector 8 is Investment Sector
Sector 9 is Manufacturing & Allied Sector
Sector 10 is Telecommunications & Technology Sector

Source: Researcher (2019)

Appendix VI: Cross Shock Transmission Linkages

Agricultural Sector	
Sectors whose volatility in any given week is influenced by the Agricultural Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Agricultural Sector's volatility in any given week**
Commercial & Services Construction & Allied Telecommunications & Technology	Automobiles & Accessories Banking Commercial & Services Construction & Allied Investment Manufacturing & Allied Telecommunications & Technology

Automobiles & Accessories Sector	
Sectors whose volatility in any given week is influenced by the Automobiles & Accessories Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Automobiles & Accessories Sector's volatility in any given week**
Agricultural Manufacturing & Allied	Automobiles & Accessories

Banking Sector	
Sectors whose volatility in any given week is influenced by the Banking Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Banking Sector's volatility in any given week**
Agricultural Energy & Petroleum Insurance	Commercial & Services Insurance Investment Manufacturing & Allied

Commercial & Services Sector	
Sectors whose volatility in any given week is influenced by the Commercial & Services Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Commercial & Services Sector's volatility in any given week**
Agricultural Banking Telecommunications & Technology	Agricultural Construction & Allied Energy & Petroleum Insurance Investment Manufacturing & Allied Telecommunications & Technology

Construction & Allied Sector	
Sectors whose volatility in any given week is influenced by the Construction & Allied Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Construction & Allied Sector's volatility in any given week**
Agricultural	Agricultural
Commercial & Services	Investment
Energy & Petroleum	
Insurance	
Manufacturing & Allied	
Telecommunications & Technology	

Energy & Petroleum Sector	
Sectors whose volatility in any given week is influenced by the Energy & Petroleum Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Energy & Petroleum Sector's volatility in any given week**
Commercial & Services	Banking
Insurance	Construction & Allied
Manufacturing & Allied	Insurance
Telecommunications & Technology	Telecommunications & Technology

Insurance Sector	
Sectors whose volatility in any given week is influenced by the Insurance Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Insurance Sector's volatility in any given week**
Banking	Banking
Commercial & Services	Construction & Allied
Energy & Petroleum	Energy & Petroleum
Investment	Manufacturing & Allied
Manufacturing & Allied	Telecommunications & Technology
Telecommunications & Technology	

Investment Sector	
Sectors whose volatility in any given week is influenced by the Investment Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Investment Sector's volatility in any given week**
Agricultural	Insurance
Automobiles & Accessories	Telecommunications & Technology
Banking	
Commercial & Services	
Construction & Allied	
Manufacturing & Allied	
Telecommunications & Technology	

Manufacturing & Allied Sector	
Sectors whose volatility in any given week is influenced by the Manufacturing & Allied Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Manufacturing & Allied Sector's volatility in any given week**
Agricultural	Automobiles & Accessories
Commercial & Services	Construction & Allied
Insurance	Energy & Petroleum
	Insurance
	Investment
	Telecommunications & Technology

Telecommunications & Technology Sector	
Sectors whose volatility in any given week is influenced by the Telecommunications & Technology Sector's shocks of the previous week	**Sectors whose Shocks of the previous week influence the Telecommunications & Technology Sector's volatility in any given week**
Agricultural	Agricultural
Banking	Commercial & Services
Commercial & Services	Construction & Allied
Energy & Petroleum	Energy & Petroleum
Insurance	Insurance
Investment	Investment
Manufacturing & Allied	

Source: Study Data (2019)

Appendix VII: Cross Volatility Transmission Linkages

Agricultural Sector	
Sectors whose volatility in any given week is influenced by the Agricultural Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Agricultural Sector's volatility in any given week**
Automobiles & Accessories	Automobiles & Accessories
Commercial & Services	Banking
Investment	Commercial & Services
Manufacturing & Allied	Insurance
	Manufacturing & Allied

Automobiles & Accessories Sector	
Sectors whose volatility in any given week is influenced by the Automobiles & Accessories Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Automobiles & Accessories Sector's volatility in any given week**
Agricultural	Agricultural
Commercial & Services	Banking
	Commercial & Services
	Manufacturing & Allied

Banking Sector	
Sectors whose volatility in any given week is influenced by the Banking Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Banking Sector's volatility in any given week**
Agricultural	Construction & Allied
Automobiles & Accessories	Manufacturing & Allied
Commercial & Services	
Energy & Petroleum	
Investment	
Manufacturing & Allied	

Commercial & Services Sector	
Sectors whose volatility in any given week is influenced by the Commercial & Services Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Commercial & Services Sector's volatility in any given week**
Agricultural	Agricultural
Automobiles & Accessories	Automobiles & Accessories
Construction & Allied	Banking
Energy & Petroleum	Construction & Allied
	Energy & Petroleum
	Insurance
	Investment
	Manufacturing & Allied

Construction & Allied Sector	
Sectors whose volatility in any given week is influenced by the Construction & Allied Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Construction & Allied Sector's volatility in any given week**
Banking	Commercial & Services
Commercial & Services	Insurance
Energy & Petroleum	Manufacturing & Allied
Investment	
Manufacturing & Allied	

Energy & Petroleum Sector	
Sectors whose volatility in any given week is influenced by the Energy & Petroleum Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Energy & Petroleum Sector's volatility in any given week**
Commercial & Services	Banking
Insurance	Commercial & Services
Investment	Construction & Allied
Manufacturing & Allied	Insurance
Telecommunications & Technology	Investment

Insurance Sector	
Sectors whose volatility in any given week is influenced by the Insurance Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Insurance Sector's volatility in any given week**
Agricultural	Energy & Petroleum
Commercial & Services	Manufacturing & Allied
Construction & Allied	Telecommunications & Technology
Energy & Petroleum	

Investment Sector	
Sectors whose volatility in any given week is influenced by the Investment Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Investment Sector's volatility in any given week**
Commercial & Services	Agricultural
Energy & Petroleum	Banking
Manufacturing & Allied	Construction & Allied
	Energy & Petroleum

Manufacturing & Allied Sector	
Sectors whose volatility in any given week is influenced by the Manufacturing & Allied Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Manufacturing & Allied Sector's volatility in any given week**
Agricultural	Agricultural
Automobiles & Accessories	Banking
Banking	Construction & Allied
Commercial & Services	Energy & Petroleum
Construction & Allied	Investment
Insurance	

Telecommunications & Technology Sector	
Sectors whose volatility in any given week is influenced by the Telecommunications & Technology Sector's volatility of the previous week	**Sectors whose Volatility of the previous week influences the Telecommunications & Technology Sector's volatility in any given week**
Insurance	Energy & Petroleum

Source: Study Data (2019)

Appendix VIII: Results of Fitting Base Models using the GARCH (1,1) Specification

Model	Sector	Variable	Coefficient	Std. Error	z-Statistic	Prob.
1	Agricultural	Mean Equation				
		R_{t-1}	0.1209***	0.0394	3.0688	0.0020
		c_m	0.0004	0.0012	0.2835	0.7770
		Variance Equation				
		c_v	0.0109***	0.0012	8.8954	0.0000
		ε_{t-1}^2	0.0417***	0.0043	9.7256	0.0000
		σ_{t-1}^2	0.9312***	0.0051	182.9010	0.0000
			R-squared: 0.009708			
2	Automobiles & Accessories	Mean Equation				
		R_{t-1}	-0.0213	0.0519	-0.4103	0.6820
		c_m	-0.0025	0.0016	-1.6226	0.1050
		Variance Equation				
		c_v	0.0003***	0.0001	4.6103	0.0000
		ε_{t-1}^2	0.2039***	0.0423	4.8181	0.0000
		σ_{t-1}^2	0.5801***	0.0714	8.1218	0.0000
			R-squared: 0.000167			
3	Banking	Mean Equation				
		R_{t-1}	0.2060***	0.0474	4.3429	0.0000
		c_m	0.027	0.2131	1.2654	0.2060
		Variance Equation				
		c_v	0.013***	0.0042	3.2381	0.0010
		ε_{t-1}^2	0.1609***	0.0466	3.4569	0.0010
		σ_{t-1}^2	0.6223***	0.1017	6.1191	0.0000
			R-squared: 0.023197			
4	Commercial & Services	Mean Equation				
		R_{t-1}	0.0899**	0.0355	2.5296	0.0110
		c_m	-0.0002	0.0011	-0.1874	0.8510
		Variance Equation				
		c_v	0.0280***	0.0059	4.6996	0.0000
		ε_{t-1}^2	0.0385***	0.0081	4.7604	0.0000
		σ_{t-1}^2	0.9162***	0.0082	112.0100	0.0000
			R-squared: 0.015315			
5	Construction & Allied	Mean Equation				
		R_{t-1}	0.0747*	0.0432	1.7296	0.0837
		c_m	-0.0006	0.0010	-0.6002	0.5484
		Variance Equation				
		c_v	0.009**	0.0042	2.1152	0.0302

		ε_{t-1}^2	0.0234	0.0245	0.9538	0.3400
		σ_{t-1}^2	0.8190***	0.1839	4.4540	0.0000
			R-squared: 0.006603			
6	Energy & Petroleum		Mean Equation			
		R_{t-1}	-0.0247	0.0452	-0.5454	0.5855
		c_m	-0.0004	0.0014	-0.3064	0.7593
			Variance Equation			
		c_v	0.007**	0.0027	2.5096	0.0120
		ε_{t-1}^2	0.0552***	0.0167	3.2240	0.0010
		σ_{t-1}^2	0.8841***	0.0340	25.9970	0.0000
			R-squared: 0.001119			
7	Insurance		Mean Equation			
		R_{t-1}	-0.1082**	0.0547	-1.9782	0.0480
		c_m	0.0017	0.0015	1.1753	0.2400
			Variance Equation			
		c_v	0.006***	0.001	6.7004	0.0000
		ε_{t-1}^2	0.3304***	0.0624	5.2967	0.0000
		σ_{t-1}^2	0.2326***	0.0813	2.8614	0.0040
			R-squared: 0.011356			
8	Investment		Mean Equation			
		R_{t-1}	-0.0319	0.0551	-0.5792	0.5624
		c_m	0.0004	0.0020	0.2117	0.8323
			Variance Equation			
		c_v	0.0046***	0.001	4.3562	0.0000
		ε_{t-1}^2	***0.2143	0.0557	3.8486	0.0000
		σ_{t-1}^2	***0.4943	0.1011	4.8888	0.0000
			R-squared: 0.001708			
9	Manufacturing & Allied		Mean Equation			
		R_{t-1}	0.0017	0.0551	0.0312	0.9750
		c_m	-0.0012	0.0016	-0.7474	0.4550
			Variance Equation			
		c_v	0.0010***	0.0001	19.0220	0.0000
		ε_{t-1}^2	0.1210***	0.0412	2.9347	0.0030
		σ_{t-1}^2	0.1319***	0.0385	3.4252	0.0010
			R-squared: 0.001901			
	Telecommunications & Technology		Mean Equation			
		R_{t-1}	-0.1197***	0.0406	-2.9524	0.0030
		c_m	0.0044***	0.0016	2.7572	0.0060
			Variance Equation			
		c_v	0.088**	0.0037	2.3304	0.0200

10		ε_{t-1}^2	0.001	0.0069	0.1441	0.8850
		σ_{t-1}^2	0.9875***	0.0086	114.2940	0.0000
			R-squared: 0.005547			

Where, for each sector:

R_{t-1} = Returns of the respective sector for week *t-1*
c_m = Intercept coefficient of the mean equation
c_v = Intercept coefficient of the variance equation
ε_{t-1}^2 = Shocks that impacted the returns of the respective sector in week *t-1*
σ_{t-1}^2 = Volatility of the respective sector for week *t-1*.

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)

Appendix IX: Results of Fitting Interaction Models using the GARCH (1,1) Models with Exogenous Variance Regressors

Model	Sector	Variable	Coefficient	Std. Error	z-Statistic	Prob.
1	Agricultural	Mean Equation				
		R_{t-1}	0.07203	0.05806	1.24072	0.21470
		c_m	-0.00088	0.00100	-0.88254	0.37750
		Variance Equation				
		c_v	0.00013***	0.00002	6.95021	0.00000
		ε_{t-1}^2	0.19020***	0.03144	6.04950	0.00000
		σ_{t-1}^2	0.62094***	0.03543	17.52731	0.00000
		$\omega_{1,t-1}$	0.04970***	0.01448	3.43216	0.00060
		$IT_{s1,t-1}$	0.00006***	0.00002	2.72413	0.00640
		$IT_{v1,t-1}$	0.00025***	0.00004	6.77527	0.00000
			R-squared: 0.01423			
2	Automobiles & Accessories	Mean Equation				
		R_{t-1}	-0.08564	0.05308	-1.61347	0.10660
		c_m	-0.00260	0.00118	-2.20280	0.02760
		Variance Equation				
		c_v	0.00889	0.00007	0.72612	0.46780
		ε_{t-1}^2	0.27020***	0.04417	6.11708	0.00000
		σ_{t-1}^2	0.32468***	0.06641	4.88893	0.00000
		$\omega_{2,t-1}$	0.97541***	0.10024	9.73109	0.00000
		$IT_{s2,t-1}$	0.00027***	0.00002	11.73921	0.00000
		$IT_{v2,t-1}$	0.07812***	0.01809	4.31078	0.00021
			R-squared: 0.001326			
3	Banking	Mean Equation				
		R_{t-1}	0.15369***	0.03562	4.31437	0.00000
		c_m	0.00161	0.00115	1.40440	0.16020

		Variance Equation				
		c_v	0.00016***	0.00006	2.78860	0.00530
		ε_{t-1}^2	0.18869***	0.05127	3.68003	0.00020
		σ_{t-1}^2	0.51133***	0.11226	4.55479	0.00000
		$\omega_{3,t-1}$	0.02068	0.01878	1.10107	0.27090
		$IT_{s3,t-1}$	0.02102***	0.00001	3.23684	0.00120
		$IT_{v3,t-1}$	0.00198	0.21691	0.08657	0.82801
			R-squared: 0.02135			
4	Commercial & Services		Mean Equation			
		R_{t-1}	0.14106***	0.03637	3.87904	0.00010
		c_m	-0.00044	0.00114	-0.38446	0.70060
			Variance Equation			
		c_v	0.01105**	0.00438	2.52078	0.01170
		ε_{t-1}^2	0.0249***	0.00604	4.12170	0.00000
		σ_{t-1}^2	1.00420***	0.00035	9.21800	0.00000
		$\omega_{4,t-1}$	0.01920***	0.00384	5.00069	0.00000
		$IT_{s4,t-1}$	0.01308***	0.00396	3.30656	0.00090
		$IT_{v4,t-1}$	0.03283***	0.00238	13.82110	0.00000
			R-squared: 0.02053			
5	Construction & Allied		Mean Equation			
		R_{t-1}	0.09536**	0.04571	2.08627	0.03700
		c_m	-0.00006	0.00107	-0.05527	0.95700
			Variance Equation			
		c_v	0.02878	0.02363	1.21815	0.22320
		ε_{t-1}^2	0.02291	0.04158	0.55092	0.58170
		σ_{t-1}^2	0.48460	0.41673	1.16287	0.24490
		$\omega_{5,t-1}$	-0.01495	0.00973	-1.53602	0.12450
		$IT_{s5,t-1}$	0.05417	1.08994	0.04970	0.96040

		$IT_{v5,t-1}$	-0.01401	0.07194	-0.19474	0.84560
			R-squared: 0.00594			
6	Energy & Petroleum		Mean Equation			
		R_{t-1}	-0.00288	0.05142	-0.05606	0.95530
		c_m	-0.00076	0.00140	-0.54135	0.58830
			Variance Equation			
		c_v	0.03312***	0.00859	3.85440	0.00010
		ε_{t-1}^2	0.15062**	0.06441	2.33869	0.01940
		σ_{t-1}^2	0.25479**	0.12644	2.01520	0.04390
		$\omega_{6,t-1}$	0.32934***	0.09412	3.49899	0.00050
		$IT_{s6,t-1}$	0.02914***	0.00349	8.35189	0.00000
		$IT_{v6,t-1}$	0.01149**	0.00558	2.05809	0.03960
			R-squared: 0.00013			
7	Insurance		Mean Equation			
		R_{t-1}	-0.11133**	0.05443	-2.04527	0.04080
		c_m	0.00123	0.00142	0.86274	0.38830
			Variance Equation			
		c_v	0.05787***	0.01321	4.38053	0.00000
		ε_{t-1}^2	0.34823***	0.06648	5.23852	0.00000
		σ_{t-1}^2	0.26814***	0.08104	3.30868	0.00090
		$\omega_{7,t-1}$	-0.03781	0.05788	-0.65317	0.51360
		$IT_{s7,t-1}$	0.07147*	0.03753	1.90449	0.05680
		$IT_{v7,t-1}$	-0.04814	0.03040	-1.58377	0.11320
			R-squared: 0.01072			
8	Investment		Mean Equation			
		R_{t-1}	-0.03480	0.05242	-0.66387	0.50680
		c_m	0.00079	0.00193	0.40743	0.68370
			Variance Equation			
		c_v	0.04915**	0.01679	2.92669	0.00340

		ε_{t-1}^2	0.18919***	0.05364	3.52735	0.00040
		σ_{t-1}^2	0.56783***	0.11343	5.00600	0.00000
		$\omega_{8,t-1}$	0.04094	0.70929	0.05772	0.95400
		$IT_{s8,t-1}$	0.05489***	0.02045	2.68440	0.00730
		$IT_{v8,t-1}$	0.01121	10.99020	0.00102	0.99930
			R-squared: 0.00159			
9	Manufacturing & Allied		Mean Equation			
		R_{t-1}	-0.02207	0.05374	-0.41071	0.68130
		c_m	-0.00021	0.00088	-0.23602	0.81340
			Variance Equation			
		c_v	0.01312*	0.00758	1.73183	0.08330
		ε_{t-1}^2	0.39129***	0.06175	6.33697	0.00000
		σ_{t-1}^2	0.29429***	0.05779	5.09203	0.00000
		$\omega_{9,t-1}$	0.20086***	0.03508	5.72552	0.00000
		$IT_{s9,t-1}$	0.02718***	0.00320	8.49892	0.00000
		$IT_{v9,t-1}$	0.04589	0.03069	1.49516	0.13490
			R-squared: 0.00057			
10	Telecommunications & Technology		Mean Equation			
		R_{t-1}	-0.10143**	0.04842	-2.09494	0.03620
		c_m	0.00363**	0.00165	2.19653	0.02810
			Variance Equation			
		c_v	0.01897***	0.00626	3.03057	0.00240
		ε_{t-1}^2	0.03234	0.02044	1.58214	0.11360
		σ_{t-1}^2	0.88603***	0.02552	34.89359	0.00000
		$\omega_{10,t-1}$	-0.03258	0.02555	-1.27541	0.20220
		$IT_{s10,t-1}$	0.02243***	0.00532	4.21583	0.00000
		$IT_{v10,t-1}$	0.04019	0.02481	1.61963	0.10530
			R-squared: 0.00460			

Where, for each sector:

R_{t-1}	=	Returns of week *t-1*
c_m	=	Intercept coefficient of the mean equation
c_v	=	Intercept coefficient of the variance equation
ε_{t-1}^2	=	Shocks that impacted the returns of week *t-1*
σ_{t-1}^2	=	Volatility of week *t-1*
$\omega_{10,t-1}$	=	Liquidity of week *t-1*
$IT_{s,t-1}$	=	Interaction term of shocks that impacted the returns of week *t-1*and the Liquidity of week *t-1*
$IT_{v,t-1}$	=	Interaction term of the volatility of week *t-1*and the Liquidity of week *t-1*

(***), (**) and (*) denotes significance at the 1%, 5%, and 10% level respectively

Source: Study Data (2019)