THE IMPACT OF GOOD NEWS AND BAD NEWS ON SOUTH AFRICA'S SECTORAL STOCK RETURN VOLATILITY: AN ASYMMETRIC GARCH ANALYSIS

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ABSTRACT

This study explores the impact of good news and bad news on South Africa's sectoral stock return volatility using an asymmetric GARCH analysis. Understanding the different impact of news on stock return volatility in different economic sectors has important implications for investors' risk management practices, portfolio allocation strategies and asset pricing.

The study employs data of daily closing prices for nine sectors and three benchmark indices for the period 2nd January 1997 – 17th August 2016. The data was split into sub-samples of pre-, during and post-global financial crisis, as well as the overall sample period. The incorporation of sub-samples was to help explain the outcomes of the overall sample period. To capture the different impact of good news and bad news on stock return volatility for each sector, asymmetric GARCH models namely, TGARCH and EGARCH were employed.

The findings from this study revealed that volatility asymmetry was present in all sectors and benchmark indices of South African equity market. Bad news had more impact on stock return volatility for all sectors except the Oil and Gas sector, than good news of the same magnitude. In the Oil and Gas sector, good news was found to have an amplified effect on return volatility compared with bad news of the same magnitude. High volatility persistence was also found to be present in the Consumer goods, Financials, Industrials, All-share index and Mid-cap index.

High differential impact of good and bad news were found in the Industrials, Financials, Basic materials, Consumer goods and the All-share index. Since the main objective of this study was to provide explanations of volatility asymmetry found in the South African sectors, the following were proposed as possible explanations of the findings. Within sectors, volatility asymmetry was explained by financial leverage, the role of the media, loss-averse investors and the behaviour of traders (overconfidence and extrapolation bias). Volatility asymmetry across sectors was explained by information flow, the uneven distribution of information by the media, investor sentiments, investor expectations and trading volumes.

Overall, the results indicate that the stock return volatility of individual sectors of the South African equity market is driven mainly by bad news (except for Oil and Gas) and that leverage effects exist in all the sectors and in the benchmark indices.

DECLARATION

Except where explicitly stated otherwise and acknowledged, this thesis is wholly my own work and has not been submitted to any other University, Technikon or College for degree purposes.

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CHAPTER 1. INTRODUCTION

The modelling of stock return volatility has been a topic of significance in the finance literature for more than four decades. Because of the wide and varying impact that stock return volatility has on the world economy, it is imperative that research in this area continues. Stock market volatility is argued to vary greatly across countries (Bakry, 2006). Equities traded in developing country capital markets tend to have different characteristics than those traded in developed countries. Developed stock markets exhibit more liquidity, efficiency and experience, which thus lowers levels of price variation and return volatility when compared to emerging stock markets. According to Aggarwal *et al.* (1999) equities traded in emerging markets exhibit distinguishing features from those traded in developed markets such as higher sample average returns, higher volatility and more predictability as well as low correlations with developed markets.

With global economic integration on the rise, stock markets around the world are becoming increasingly volatile. For this reason, the interest shown in stock market volatility in emerging economies has also been increasing rapidly. Emerging markets relevance to the global portfolio managers as an investment alternative has increased (Bakry, 2006), due to diversification opportunities that can be exploited (Hartmann and Khambata, 1993). Despite these characteristics of emerging markets in comparison to the developed markets, existing literature on stock return volatility in emerging markets is scanty. In this regard, the examination and modelling of stock return volatility in an emerging market such as South Africa has the potential to provide further insight to the understanding of stock market behaviour.

1.1 Research Context

Economic theory states that stock prices incorporate all currently available information. This leads to the belief that stock price movements will be relatively smooth and gradual as economic information changes slowly (Blasco *et al.*, 2002). Individual shares may be impacted by new company specific information, such as a change in the gold price for a gold mine, but overall prices should have low volatility. Yet evidence around the world shows that prices sometimes change dramatically, either upwards or downwards (Funke and Matsuda, 2006). They do this as a result of "news" that enters the market. In this context "news" refers to economic news, company-specific news, political news or any new information that enters the market. This news should have an impact on one or more of the three "primitive factors" that influence stock prices. According to Boyd *et al.* (2005), these three "primitive factors" are the risk-free rate of interest, the expected dividend/earnings growth rate and the risk premium.

The theoretical background that explains the interaction of "good news" and "bad news" with stock returns is based on asset pricing theory, the efficient market hypothesis and behavioural finance. Asset pricing theory, which encompasses the Arbitrage Pricing Theory (APT), quantifies the risk premia associated with various economic factors that influence the returns on assets (Maysami *et al.*, 2004). Unanticipated announcements may affect stock prices positively or negatively, thus causing volatile movements in stock returns. Paavola (2006) argues that APT consists of two types of risk, namely systematic risk (which cannot be diversified away) and non-systematic risk (which is unique to each sector or security and can be diversified away). Understanding differences in the type of risk for each sector of the equity market, why sectors behave in a particular manner and the impact of both good news and bad news on stock return volatility in those sectors will help establish the optimal investor behaviour in each sector.

The efficient market hypothesis (EMH) forms part of traditional finance theories. It suggests that security prices include all the information currently available and that prices respond only to true news (Funke and Matsuda, 2006). The EMH theory assumes, therefore, that capital market investors cannot use information and historical data presented by the market to earn returns that are above average (Fama, 1998). If news releases are congruent with investor expectations, stock prices should not respond to this news. The only news releases that should impact on stock market volatility are those that are surprises. According to Funke and Matsuda (2006), the surprise announcements represent "true news". The impact on stock prices depends on whether the "true news" entering the markets is good (positive) or bad (negative). Criticisms of the EMH such as underestimates the dangers of bubbles, treating information as an objective commodity and focusing only on the demand side of the market, led to increased support of behavioural finance theory.

Bailey (2005:86) states that "the quest for ways to account for asset price volatility has pursued a variety of routes, most of which now shelter under the umbrella of behavioural finance". According to Uygur and Tas (2014), behavioural finance is a new approach to the field of financial markets and has emerged due to complications faced by traditional finance theory. This new approach allows an understanding of the sometimes seemingly irrational interpretation of information by some investors. Behavioural finance suggests that financial phenomena such as long-run reversal can be better understood by using models in which some investors are not rational and prediction patterns are based on valuation parameters, short-term momentum and firm characteristics (Uygur and Tas, 2014).

Behavioural finance is of particular interest in providing the theoretical backdrop to this study. Behavioural finance places great emphasis on why investors trade, the selection of assets to form portfolios by investors and why returns vary across shares as a result of other factors other than risk factors mentioned in traditional finance theory (Subrahmanyam, 2007). This theory, it is argued, rests on two foundations, namely investor sentiment and practical limits to arbitrage. The former explains how investors might cause irrational prices to occur whereas the latter explains why such misprices are not easy to correct (Howells and Bain, 2008:553). Given the amount of information entering the stock market on a daily basis, a suggestion can be made that stock return volatility can be impacted positively or negatively by many different forms of news. The above-mentioned foundations enable us to try to deduce the drive behind investor reaction to positive and negative news entering the market and how such reaction will impact on stock return volatility in each sector.

To date, research has been done on the impact of good and bad news on stock return volatility in developed and developing countries, including South Africa. Most studies that examined the impact of news on stock prices focused on a particular sector in isolation. For example, Funke and Matsuda (2006) studied the financial sector, Diaz and Jareno (2009) the industrial sector, Syriopoulos *et al.* (2015) both the industrial and financial sectors and Suleman (2012) eight sector indices, namely oil and gas, financial, basic material, utilities, food and beverages, healthcare, industry, automotive and parts. In developed countries, studies were conducted in countries that are highly industrialised such as the US, Germany, UK, Japan and Spain. Findings from most of the studies done for developed countries indicated that bad news increases volatility more than good news of the same magnitude (Laakkonen and Lanne, 2008; Chen *et al*., 2003; Dulwich 2006; Boyd *et al*., 2005; Patton and Sheppard, 2015; Funke and Matsuda, 2006).

Studies on the impact of good news and bad news on stock return volatility have also been extended to developing countries. The countries in which such studies were conducted include China (Hou, 2013), Hong Kong, South Korea, Singapore, Malaysia, Taiwan and Thailand (Liau and Yang, 2008), Pakistan (Suleman, 2012) and Lebanon (Bouri and Salloum, 2015). Except for a study done for Pakistan, findings from developing countries also confirmed that volatility asymmetry was negative, thus supporting findings from developed countries that bad news increases stock return volatility more than positive news.

Mangani (2008) conducted a study for South Africa in which the main focus was examining the risk-return relationship of forty-two individual stocks and two portfolios. GARCH type models were employed and the results showed that there was limited evidence of leverage effects and asymmetry in volatility for both portfolios and most of the stocks. In contrast to Mangani (2008), Chinzara and Aziakpono (2009) found volatilities of the aggregate and four main sectors of the South African stock market to be asymmetric. Mandimika (2010) focused on the relationship between volatility and risk return. Furthermore, the study analysed the behaviour and long-term trend in volatility using aggregate, individual and sectoral data. Chinzara (2011) analysed how systematic risk arising from the macro economy is transmitted into stock market volatility. The study also employed both aggregate stock indices and sectoral indices.

Another study by Mandimika and Chinzara (2012) for South Africa showed that there was significant evidence of asymmetry and leverage effects in all sector returns. Arguile (2012) found that Basic materials, Oil and Gas, Telecommunications and Consumer services were the sectors that had negative news with a greater impact on volatility than positive news of the same magnitude. Niyitegeka and Tewari (2013) found volatility to be persistent and that asymmetric effects of news on conditional volatility are not prevalent in the Johannesburg Stock Exchange (JSE).

To the author's knowledge, not much literature exists for South Africa on the impact of good news and bad news on stock return volatility in different sectors, as opposed to for the market as a whole. This study starts to fill that gap by examining the impact of good and bad news on sectoral stock return volatility of the JSE. Although other empirical studies (see, Mandimika and Chinzara, 2012), have also examined the asymmetry of South African sectors, the current study employs more recent data, including the post 2007 financial crisis period and also attempts to provide explanations of why various sectors' return volatility varies when news enters into the market.

Markets receive vast amounts of information on a daily basis, which could have a greater impact on the stock return volatility and risk profiles of investors. Any form of knowledge that aids in helping investors to reduce the level of this risk exposure is of great importance. This study on the impact of good news and bad news on sectoral stock return volatility will not only help in trying to reduce the risk for investors, but will also aid in improving the efficiency in the South African stock market. An efficient stock market suggests that more investors will be encouraged to invest in the economy thus increasing investment and capital inflows.

According to Van Wyk (2015), the JSE is the largest stock market in Africa and it offers global diversity hedging opportunities for many foreign investors. Understanding the impact of good and bad news on stock return volatility in different economic sectors will help investors to manage risk better through devising effective portfolio diversification strategies. Rangel (2011) states that the response of asset prices and market volatility to news releases concerning fundamental variables is of key importance for relevant economic and financial decisions, such as asset pricing, risk management and portfolio allocation. Given the volatility of the equity market, problems of financial and macroeconomic instability are inherent. This means that policymakers face challenges in trying to create a conducive environment for investors. Therefore, it is imperative that a study of the impact of good and bad news on stock return volatility at a sectoral level should be done.

1.2 Goal of the Research

The main goal of this research is to investigate the impact of good and bad news on stock prices in South Africa and whether this impact differs for various sectoral stock market indices and the overall indices.

1.3 Methods, Procedures and Techniques

Financial data is characterised by leverage effects and volatility clustering hence the use of linear structural models cannot adequately capture these properties (Brooks, 2008). In light of this, Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models allow for the conditional variance to be dependent upon previous own lags, are parsimonious, avoids over fitting and the model is less likely to breach non-negativity (Brooks, 2008). However, GARCH models enforce a symmetric response of volatility to positive and negative shocks. In this regard, informed by previous empirical studies (Mandimika, 2010; Mandimika and Chinzara, 2012; Chinzara, 2011; Chinzara and Aziakpono, 2009; Funke and Matsuda, 2006; Uygur and Tas, 2014; Blasco *et al.*, 2005; Suleman, 2012), asymmetric GARCH models, in particular the Exponential-GARCH (EGARCH) and Threshold-GARCH (TGARCH), models will be employed to capture the asymmetric impact.

According to Enders (2010), the EGARCH and TGARCH models allow for shocks to have different effects on volatility. This means that the effects of good news and bad news on stock return volatility for each sector can be captured by employing these models. Good news and bad news will be observed in the sign of the error term. A comparison of the sectoral mean stock returns and conditional volatilities will be undertaken to observe if the impact of good and bad news is similar or varies across sectors.

The data was obtained from Thompson Reuters Eikon. Daily closing data from January 1997 to August 2016 for the JSE/FTSE All-Share price index, JSE/FTSE Small Cap index, JSE/FTSE Mid Cap index and the following sectoral indices: JSE/FTSE Consumer Goods index, JSE/FTSE Consumer Services index, JSE/FTSE Industrial index, JSE/FTSE Basic Material index, JSE/FTSE Health Care index, JSE/FTSE Technology index, JSE/FTSE Telecommunication index, JSE/FTSE Oil and Gas index and JSE/FTSE Financial price index. As is practice in standard empirical literature, the daily index series was converted to continuous compounded returns, consistent with Chinzara and Aziakpono (2009), Mandimika and Chinzara (2012) and Rangel (2011). Sectoral indices are argued to provide useful information that market players employ to form style investment strategies and evaluate portfolio allocation decisions (Syriopoulos *et al.*, 2015), hence their use in this study.

1.4 Organisation of the study

The remainder of the study is as follows. Chapter two introduces the theoretical framework that underlies the financial market and in particular the behaviour of the stock market. To begin the discussion, the asset pricing model is introduced first because it provides the foundation for determining an asset's price given a certain level of risk. The chapter examines the two asset pricing models namely, Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Due to the limitations of these two models, an alternative theory which also helps to understand how investors behave when information is transmitted into the market is the Efficient Market Hypothesis (EMH). This is examined next. Last to be examined is the Behavioural Finance (BF) theory which is pertinent to this study because it attempts to explain deviations of stock returns from their mean by taking into account investor behaviour driven by non-fundamental factors.

Chapter three provides empirical evidence on the modelling of volatility on stock returns using GARCH models. The chapter is divided into empirical studies from developed and developing countries. Due to the different characteristics of the equity markets in developed and developing countries, it was imperative to examine them differently for comparison purposes. Studies on South Africa were also examined so as to identify gaps in the literature for this study to address. Chapter four describes the method, procedures and techniques employed in this study to enable the achievement of the set objectives. The results of the empirical analysis are given in Chapter five. The chapter will report on the findings and then a discussion on the findings will follow. Finally, Chapter six provides the summary and conclusion of the study. It starts with a brief overview of previous chapters and then follows with the implications of the study on investors and policy makers then outline the areas of further research.

CHAPTER 2. THEORETICAL FRAMEWORK

2.1 Introduction

This chapter analyses the theoretical background that explains the interaction of good and bad news with stock prices but a brief overview of the Johannesburg Stock Exchange will be provided first to help understand the major sectors that drive this exchange. The theoretical background is based on asset pricing theory, the efficient market hypothesis and behavioural finance. An examination of the Asset Pricing Models and Efficient Market Hypothesis (EMH) will be done first followed by an in-depth examination of the Behavioural Finance (BF) approach.

2.1.1 Johannesburg Stock Exchange (JSE) context

The JSE was founded in 1887 by Benjamin Woollan, primarily to provide a facility through which investors could buy and sell shares after the discovery of the Witwatersrand gold fields and the subsequent formation of the mining and investment companies (Johannesburg Stock Exchange, 2017). The JSE was demutualised in 2005 and became a listed company. According to Mabhunu (2004) the main reason for this was to improve the efficiency of the exchange and also to increase its competitiveness on a global scale. As a result of this listing the JSE has played a pivotal role in helping the South African economy to grow. According to Johannesburg Stock Exchange (2017), the JSE is currently ranked the 19^{th} largest exchange in the world by market capitalisation and the largest exchange in the African continent.

Since its inception, the JSE has gone through many vast changes thus enabling it to help steer growth in the South African economy through allowing companies to raise capital for investments. According to Yartey and Adjasi (2007) stock markets provide an avenue for companies to raise capital at low costs, reduce the risk of credit crunch as companies are less reliant on bank financing and also the encourage savings thus boosting domestic savings. The JSE offers secure, efficient primary and secondary capital markets across a diverse range of securities, supported by post-trade and regulatory services (Johannesburg Stock Exchange, 2017). Many companies in South Africa are listed on the JSE and these companies belong to various sectors.

According to Mayer (2013) they are nine sectors in South Africa and the classification is derived from the Industry Classification Benchmark (ICB). These sectors are listed in Table A1 found in the Appendices. It was noted by Mayer (2013) that the Basic materials sector is the largest component of the JSE with 26% of the total value of all companies listed on the JSE contributing to this sector. The second largest contributor to the JSE market capitalisation is the Financials and Consumer services sector. Both sectors make up 20% each of the total value of the JSE-listed companies. Consumer goods follow at 16%, Industrials (5%), Telecommunications (4%), Health Care (3%), Oil and Gas (3%) and Technology (3%) (Mayer, 2013).

However, the size of the sector does not provide adequate information about the performance of each sector. The global financial crisis of 2008 had a huge negative impact for each and every sector in South Africa. The after-shock effects of the crisis are still being experience in some of the sectors. Mayer (2013) found that the Basic material sector recorded the least growth of 4.8% in market capitalisation over a five year period after the crisis. The main possible suggestion for this low growth is the low commodity prices which reduced the profit margins to loss making levels in mining and also strikes which curtailed the production of commodities (Mining Review Africa, 2015). The Health Care sector recorded the highest growth rate of 210% in market capitalisation after the crisis, followed by the Consumer goods (177%), Technology (109%) and Consumer services (107%). Other sectors namely Industrials, Oil and Gas, Telecommunication and Financials recorded market capitalisation growth rates of 15%, 24%, 24% and 67% respectively. A plausible explanation for low growth rate in market capitalisation in these sectors can be as a result of the poor performance of the South African economy. After the financial crisis the South African economy has been experiencing a sluggish growth path. Sectors such as the Industrials and Financials are heavily influenced by the performance of the economy as a whole. The poor performance of the economy suggests that consumers are left with low disposable income and they are also likely to default on loan payments. This will then have adverse effects for companies in these sectors because of low profits being generated. The ultimate impact of this bad news would be experienced in the stock market as investors earn low yields. This brief overview of the JSE will aid in providing explanations of the findings of this study.

2.2 Asset Pricing Models

The two asset pricing models that are widely used in finance are the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT).

2.2.1 The Capital Asset Pricing Model

The earliest advocates of the CAPM were Sharpe (1964) and Lintner (1965). They based this model on the theory that not all risks should affect asset prices. Sharpe (1964) and Lintner (1965) developed this CAPM as an extension of Markowitz' model of portfolio choice. According to Fama and French (2004), this model of portfolio choice assumes that investors are risk averse and their only concern is the mean and variance of their investment return for a single period. Investors thus choose portfolios that are mean-variance efficient. This means that they maximise expected asset returns given the variance of portfolio return and they also minimise the variance, given the expected return of the asset.

To identify a portfolio which is mean-variance efficient Sharpe (1964) and Lintner (1965) added two more assumptions to the Markowitz model namely, that investors can borrow and lend at a risk-free rate regardless of the amount being borrowed and, secondly, that investors are in complete agreement on the joint distribution of assets returns (Fama and French, 2004). The CAPM states that "the rate of return on an asset will be equal to the risk-free rate plus a risk premium which depend upon the market price of risk and the quantity of market price risk and the quantity of market risk contained in the asset" (Howells and Bain, 2008: 247). The formula of the CAPM expressed by Sharpe (1964) and Lintner (1965) is as follows;

$$K_i = K_{rf} + \beta_i (K_m - K_{rf})$$

where K_{rf} is the risk-free rate of return which is seen as the baseline from which all other rates are derived by addition of a premium (Howells and Bain, 2008). If this rate rises then the returns of all risky assets should also be pushed up by the same margin. K_i is the expected return on asset i, β_i measures the asset's exposure to the variation of the market rate of return and lastly, $(K_m - K_{rf})$ represents the market price of risk from which the premium to be paid on each asset is determined.

The equation above is known as the security market line (SML) which shows the additional return on an individual's assets with risk characteristics that are comparable to those of the whole market portfolio (Howells and Bain, 2008). The CAPM notes that if the assets are fairly priced, they yield a rate of return such that they plot on the SML (Sharpe, 1964).

The CAPM model has its fair share of criticism arising from its assumptions. One of the primary criticisms is the assumption of unrestricted risk-free borrowing and lending (Fama and French, 2004). In the real world, this assumption does not hold because there is always an element of risk inherent in every transaction - for example, default risk on a loan, or changes in the rate of interest on borrowed funds.

Another criticism arises from the single period nature of the CAPM (Merton, 1973). In this regard, Merton (1973) developed the Intertemporal CAPM, which assumed that investors trade continuously and act to maximise the expected utility of lifetime consumption. However, this extended model still shares some assumptions with the Sharpe (1964) and Lintner (1965) CAPM, thus making it susceptible to the same criticisms (Arguile, 2012).

2.2.2 The Arbitrage Pricing Theory (APT)

Ross (1976) introduced the arbitrage pricing theory as an extension of the CAPM but employed fewer assumptions. According to Oberuc (2011:21) "the APT states that the return of a risky asset such as stock is a linear function of a number of macroeconomic and financial factors". This theory relies on a number of assumptions namely, perfect market competition, investors have homogenous expectations, investors are both risk averse and insatiable with regards to their level of wealth and lastly, the returns are generated according to a linear model with k number of factors (van Rensburg, 1997).

Roll and Ross (1984) are of the opinion that the APT is only affected by a few systematic factors which influence the long-term average returns of financial assets. While not denying that asset price volatility is influenced by many factors, the APT is said to focus on those factors that have a great effect on the entire portfolio. Idiosyncratic factors have been identified as those factors that have an effect on asset returns, but they cannot explain volatility in market returns (Roll and Ross, 1984). The APT, however, places little emphasis on these factors, as their impact on returns of assets can be cancelled out through diversification. Huberman and Wang (2005) state that a linear relationship between factor betas and the expected return on assets exist only if equilibrium prices offer no arbitrage opportunities.

In the APT, the majority of portfolio risk can be explained by systematic factors applicable to the general economy (Roll and Ross, 1984). For this reason, the APT makes use of several beta values to compare the returns of individual stocks with that of the market as a whole. In contrast, the CAPM employs a single beta value. However, portfolio performance is varied as a result of different levels of sensitivity to these factors.

The APT is moreover not restricted to the single period case of the CAPM and for this reason both single period and multiple period cases hold. Unlike the CAPM, which investigates sensitivities to the market return, APT measures the sensitivities of many factors (Arguile, 2012). In the APT, there is also no requirement that the market portfolio should be mean-variance efficient (Patterson, 1995).

Another major difference between the CAPM and APT identified by Rolls and Ross (1984:17) is that the APT states that "any market equilibrium must be consistent with no arbitrage profits and every equilibrium must be characterised by a linear relationship between each asset's expected return and its returns loadings on the common factors".

The APT quantifies the risk premia associated with various economic factors that influence the returns on assets (Maysami *et al.,* 2004). Paavola (2006) argues that APT consists of two types of risk, namely systematic risk (which cannot be diversified away) and non-systematic risk (which is unique to each sector or security and can be diversified away). Understanding differences in the type of risk for each sector, why sectors behave in a particular manner, and the impact of good news and bad news on stock return volatility in those sectors will help establish the optimal investor behaviour in each sector. Since the APT argues that only systematic risk explains the market variations of returns, Chen, Roll and Ross (1986) identified the following macroeconomic and financial variables as being important: inflation rate, aggregate consumption, the return on an equity index, unexpected changes in the term structure of interest rates, the growth rates of industrial production and a measure of the private sector's default premium.

A simplified three or four factor model of the APT was devised by Roll and Ross (1984) and is shown below;

$$R_{it} = E_i + b_{i1}f_{1t} + b_{i2}f_{2t} + b_{i3}f_{3t} + b_{i1}f_{1t} + \ldots + b_{ik}f_{kt} + e_t$$

where R_{it} represents the return on asset i at time t, the coefficient of b_{i1} to b_{ik} represents the sensitivity of asset i's to changes in the factors f_{1t} to f_{kt}, the term E_i, is the expected value over time on the i^{th} asset and lastly, e_t is the noise term which shows the unsystematic risk component idiosyncratic to the i^{th} asset (Mandimika, 2010).

Like any other theory, the APT is also characterised by its own limitations. According to Huberman and Wang (2005), the APT's major weakness is that it does not specify the factors to include and, as a result, different studies employ various sets of factors which lead to unique and contrasting findings. A further limitation is that it requires an extension of the original model (i.e. the CAPM) which violates the APT's core assumption of assets being priced as if there are no arbitrage opportunities in markets.

2.3 Efficient Market Hypothesis (EMH)

The EMH is a classical traditional finance theory which postulates that the prices of stocks reflect all the available information concerning the risk and return of those stocks. According to Baker and Wurgler (2006), this theory argues that rational economic agents force capital market prices to equate to the discounted future cash flows of investments. The main advocate for the EMH theory was Fama (1965) and this became a widely accepted theory concerning financial market activities. Fama (1965) defined an efficient market as one in which actual security prices represent precise estimates of their intrinsic values at all times. The theory states that due to market efficiency investors cannot earn higher than average returns when investing.

The EMH is built around the fundamental assumptions of financial markets (Howells and Bain, 2008). The first assumption is that not all investors are rational, but their irrationality is likely to cancel each other out, leaving market prices to be valued according to the informed traders looking for unexploited profit opportunities. This is possible because market prices will be driven by the process known as arbitrage (Baker and Wurgler, 2006). The second assumption is that investors are assumed to form rational expectations, because they possess all the relevant information needed to make informed decisions about future movements in the market. Lastly, the EMH states that despite numerous uninformed investors forcing financial assets prices to deviate from their fundamental level, arbitrageurs would identify such an anomaly and would trade accordingly, forcing the price to return to its fair value (Howells and Bain, 2008)

Fama (1970) identified three forms of market efficiency on which the EMH can be said to hold. These are weak, semi-strong and strong market efficiency. In the weak form of market efficiency, all information contained in the past behaviour of the security's price is incorporated. This implies that studying the past information trend will not enable us to make concrete judgements on future asset price movement (Howells and Bain, 2008). Since this information is available to the public, the power of predicting future price movements is limited.

The semi-strong form of market efficiency states that all publicly available information is reflected in current share prices (Howells and Bain, 2008). Investors cannot make any excess gains by employing such information in their trades. Fama (1970) notes that the freely available information includes, amongst others, annual reports, balance sheet composition, new security issues and stock splits, etc.

Lastly, in the strong form market efficiency, share prices include all information, public or private. This means that investors are unable to enjoy excess returns by employing such information. This form of market efficiency has been regarded as the most demanding of them all because it is impossible for investors to make excess returns on insider trading information (Howells and Bain, 2008).

In order for the EMH theory to hold, certain market conditions should be met. According to Fama (1970), there should be zero transaction costs or taxes on the trading of shares, all market participants should access new information without incurring any costs and investors should have homogenous expectations about the effects of current information on future share prices. Furthermore, Fama (1970) argued that even if these assumptions do not hold in the real world, markets will still achieve efficiency.

A number of practical shortfalls of the EMH have been identified. Firstly, the EMH theory focuses mainly on monetary exchange and the demand side of the market (Ball, 2009). This theory does not factor in supply side queries such as the credibility and validity of information entering the market and the volume of information being made available. A second limitation is that the EMH treats information as an objective commodity (Ball, 2009). This means that due to variations in investors' beliefs, new information will have many different interpretations which will result in rapid price changes.

Lastly, the EMH theory is said to underestimate the dangers of asset bubbles (Ball, 2009). In one of its assumptions, the EMH argues that all available information is reflected in current share prices. Hence, regulators are less inclined towards verifying the intrinsic value of overpriced securities, leading to the failure in identifying bubbles earlier.

These weaknesses in the EMH, especially its failure to explain market anomalies, have given rise to increased support for the behavioural finance theory, which incorporates the effects of investor sentiments in stock price formation. Proponents of the EMH defend it by arguing that, behavioural finance cannot be tested and is in fact not a theory but a collection of ideas and results (Ball, 2009). For this reason, it is suggested that behavioural finance cannot replace the EMH, but can work in conjunction with it to explain pricing variations in assets.

2.4 Behavioural finance (BF)

"The quest for ways to account for asset price volatility has pursued a variety of routes, most of which now shelter under the umbrella of behavioural finance" (Bailey, 2005:235). According to

Uygur and Tas (2014), behavioural finance is a new approach to the field of financial markets and has emerged due to complications faced by traditional finance theory. This new approach allows an understanding of the sometimes seemingly irrational behaviour of some investors as a result of their interpretation of information. Behavioural finance suggests that financial phenomena such as long-run reversal can be better understood by using models in which some investors are not rational, in addition to prediction patterns based on valuation parameters, short-term momentum and firm characteristics (Uygur and Tas, 2014).

Behavioural finance is said to place great emphasis on why investors trade, the selection of assets by investors to form portfolios and the variation of share returns as a result of factors other than the risk factors mentioned in traditional finance theory (Subrahmanyam, 2007). The underlying assumption of behavioural finance is that information structure and the characteristics of market participants systematically influence individual investment decisions as well as market outcomes (Baker and Nofsinger, 2010). The human brain, it is argued, uses emotional filters and shortcuts and, hence, such processes may influence financial decisions to the extent that people seem to be acting irrationally. This violates traditional concepts of risk aversion and, consequently, predictable errors are made in forming forecasts about future markets movements.

As background, the standard (or neoclassical) economics arguments about rational behaviour is based on some fundamental assumptions, namely, that people are utility and profit maximisers, that people make use of all the information available to make investment decisions, that there are many buyers and sellers without the ability to influence the price of assets and, lastly, that investors have rational preferences across possible outcomes or states of nature (Ackert and Deaves, 2010). Behavioural finance criticises the last two assumptions of atomistic investors and their rational expectations (Forbes, 2009). Traders in the financial markets are said to be driven not exclusively by the fundamental news but by issues such as social, emotional and psychological forces that can also influence investor decision making. Empirically, the evidence suggests that investors are not fully rational in their behaviour because of the presence of market anomalies that continuously exist (Barberies and Thaler, 2003; Shleifer and Summers, 1990). The demand for risky assets is mostly affected by investors' beliefs or sentiments. Ackert and

Deaves (2010) identified four key themes that characterise behavioural finance. These are heuristics, framing, emotions and market impact.

Behavioural finance theory rests upon two models, namely the noise trader model and the representative agent model. Noise traders are defined as stock traders that do not possess inside information and make irrational investment decisions based on their beliefs and sentiments (Uygur and Tas, 2014). Trading activities of such investors result in stock price deviations from their fundamental levels. According to Forbes (2009), the noise trader model consists of two types of investors, informed and uninformed, or "smart" and "dumb" traders. Informed or smart traders are those investors that rely on fundamental information to make informed decisions about investment. They are also known as rational investors. Despite the presence of rational investors in the market, the actions of noise traders have been found to sometimes swamp the market. Forbes (2009) found that market anomalies which have arisen during the course of history (for example, asset bubbles or frenzies) were as a result of noise traders. The modelling structure of these anomalies included optimism, herding, momentum, asymmetric attitudes to gains and losses and overreaction and under-reaction to news (Barberis and Shleifer, 2003; Froot *et al.,* 1992; Daniel *et al.,* 1998).

According to Howells and Bain (2008), behavioural finance theory rest upon two foundations, namely investor sentiments and practical limits to arbitrage. The former explains how investors might cause irrational prices to occur, whereas the latter explains why such misprices are not easy to correct (Howells and Bain, 2008). In order to fully understand the importance of arbitrage, the theoretical foundations of the traditional finance theories have to be considered. These foundations are that investors are rational, that irrational trades by noise traders cancel out and leave returns and prices to be determined by rational traders, and, lastly, that profitable opportunities for arbitrage force noise traders out of business. Traditional theories argue that arbitrageurs (or rational investors) trade to assure that relative prices of securities are in line for there to be no riskless arbitrage opportunities (Shleifer and Summers, 1990). Behavioural finance challenges this notion of arbitrage by arguing that riskless arbitrage dealing is only applicable in theory and not in practice. Howells and Bain (2008) argue that, in the real world, arbitrageurs are forced to take risks which limit their ability to address the mispricing of assets.

The practical limitations to arbitrage were identified by Shleifer and Summers (1990). They found that traders often find it difficult to obtain close substitutes for the assets which are overpriced thus causing them to trade with imperfect substitutes. Howell and Bain (2008) went further to argue that due to time constraints the imperfect substitutes may result in unforeseen price divergence rather than convergence, increasing the risk of losses for arbitrageurs. For these reasons, the concept of riskless hedges for the arbitrageur becomes questionable. Shleifer and Summers (1990) identified the two types of risk that limit arbitrage as fundamental risk and unpredictability of the future resale price. The idea of selling overvalued stocks is limited by the knowledge that the market might improve, and by the fact that, arbitrageurs' fear of losses limits the ability of short-selling to drive prices down to their fundamentals. The resale price risk depends on the arbitrageur having a finite horizon (Shleifer and Summers, 1990). Trading costs, including transaction cost, limits rational arbitrageurs to having short horizons. This means that there are limited resources dedicated to long-term arbitrage against fundamental mispricing.

Argyros (2012) found that only a few market experts are able to conduct arbitrage. For this reason, if assets prices have deviated very far from the fundamentals then arbitraging will not be possible. The limited number of experts will not have sufficient resources to correct the mispricing.

Another limitation for arbitrage identified by Shleifer and Summers (1990) was that arbitrageurs are presumed to know the fundamental value of a security, but this is not always the case. This reality makes arbitrage even riskier than before and thus arbitrage opportunities are limited. In addition, arbitrageurs are funded by external sources that have limited knowledge of arbitrage and for this reason the amounts of funds available to them for arbitraging are limited. Shleifer and Vinshy (1997) argue that outside investors are less willing to allocate large resources to arbitrageurs since they cannot identify good and bad arbitrageurs. Arbitrage opportunities are also limited due to the fact they run the risk of losing these funds if performance is poor, thus causing them to be reluctant to take large positions.

Investor sentiment is the second foundation of behavioural finance and can be defined as the propensity to speculate (Baker and Wurgler, 2006). According to Argyros (2012), traditional finance theory does not include the concept of investor sentiment because changes in demand are said to be the result of the arrival of external information about future cash flows and interest rates. Over the years, however, the perceived role of investor sentiment has played a very crucial role in explaining the behaviour of traders. The concept of investor sentiment was first brought to light by Keynes (1936) when he asserted that investment was driven by "animal spirits" (Argyros, 2012). To understand the concept of investor sentiment Howells and Bain, (2008) note that behavioural finance draws its inspiration from the work of psychologists.

Shleifer and Summers (1990) suggests that noise traders lack fundamental information to make informed decisions and therefore they employ sentiments based on pseudo-signals. Their actions are in most cases correlated, which leads to aggregate demand shifts that might result in stock prices deviating from their fundamental values. Since decisions about investment are based on noise and strategies employed are based on inflexible trading strategies, such investors are prone to errors which might lead to systematic risk.

Shleifer and Summers (1990) note that psychology literature documents that people's decisions driven by sentiment arise from being overconfident, putting too little weight on base rates and too much weight on new information. Cognitive psychology recognises that a number of biases play an influential role in the way investors evaluate assets and make investment decisions. Howells and Bain (2008) identified two investor biases capable of mispricing assets; namely, conservatism and representativeness. Conservatism is defined as a situation where individuals do not, or are slow to update their beliefs, as rational Bayesians would in the face of new evidence (Howells and Bain, 2008). The reason for this is because new information that differs from the existing information held by investors is hard to accept. Tversky and Kahneman (1974) define representativeness heuristic as the phenomenon that people look for a pattern in a series of random events. This leads to people generalising and drawing conclusions on the basis of too little information. The possibility of randomness is discounted and this sometimes leads to investors under-or overreacting to certain information.

Prast (2004) identifies the following judgement biases which also contribute to investors being capable of mispricing assets; overconfidence, self-serving bias and biased self-attribution, cognitive dissonance and availability heuristic. These biases influence investors to act irrationally when devising investment strategies or making investment decisions, which leads to deviations of asset prices from their fundamental levels.

Empirical evidence also suggests that investor sentiments have a different impact on conditional volatility in different sectors of the economy. Uygur and Tas (2014) discovered that the conditional volatility of the industry and banking sectors are more vulnerable to increases in investor sentiments, whereas the retail and telecommunication sectors are least affected. They argue that the banking and industry sectors are the key driving sectors of economies and so noise traders monitor them closely.

Criticisms of behavioural finance theory were raised by proponents of traditional finance theories. According to Subrahmanyam (2007) the common criticisms of behavioural finance are that it is restricted and focuses only on certain facets of finance, that extensive data mining was adopted in discovering weaknesses in traditional finance theories and, lastly, behavioural finance failed to stipulate concrete asset pricing models that can link equity returns and investor sentiments. In their defence, advocates for the behavioural finance argue that this model is based on how individuals behave based on extensive empirical evidence and they explain the evidence better than the traditional models.

2.5 Summary

The theoretical frameworks reviewed include the efficient market hypothesis (EMH), the asset pricing models including the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) as well as behavioural finance (BF). The EMH is the traditional finance theory and postulates that asset prices include all the information available and that investors cannot make profits that are above the fundamental levels. However, this theory is criticised for its simplified assumptions that are difficult to comprehend in real world situations thus giving rise to the behavioural finance (BF). Advocates of behavioural finance argue that this new theory employs investor sentiments to explain the continued existence of market anomalies that cannot be explained by the EMH.

The other two asset pricings models that stem from modern portfolio theory and are widely used in finance are the CAPM and the APT. The CAPM is the most employed of the two, because of the simplicity of its assumptions. However, the APT has started to gain ground on the CAPM because it allows for an explanatory rather than a statistical model of asset return and it also assumes that each investor will hold a unique portfolio with its own set of betas.

CHAPTER 3. EMPIRICAL EVIDENCE

3.1 Introduction

This chapter discusses the empirical evidence of the impact of good and bad news on stock return volatility. A brief summary of empirical evidence of event studies done on the impact of good and bad news on stock return volatility will be done first. However, it should be borne in mind that while many of these studies are not of direct relevance to this particular study, they provide background information of what good and bad news may entail for financial markets. These event studies also allow a clear picture of how the nature of news entering the market daily influences stock returns. In this study, the error term is the indicator of both good and bad news that will affect stock return volatility. Empirical evidence from developed economies will be discussed first, followed by evidence from developing economies. The separation of studies into these categories enables us to identify if there are any differences or similarities in the impact of good and bad news on stock return volatility across developed and developing countries.

A study done for the US and Germany by Funke and Matsuda (2006) analysed the similarities and differences in the impact of macroeconomic news on stock return. Using the EGARCH, it was found that bad news increased return volatility more than the good news of the same magnitude. Funke and Matsuda (2006) also found a higher than unexpected unemployment rate (bad news) had a positive impact on stock prices that in the US during the boom period (January 1997-March 2001), and a negative impact in the recessionary period (April 2001 – June 2002). Boyd *et al.* (2005) conducted another study for the US which focused on the short-run response of stock prices to unemployment news. Boyd *et al.* (2005) found that during the contraction period good news (lower than expected unemployment rate) had a positive impact on stock returns whereas bad news (higher than expected unemployment rate) had a negative impact. The expansionary period showed that bad news had a positive impact on stock returns whereas good news had a low and negative impact.

Dulwich (2006) found that events that cause extreme decreases in volatility change total stock return much lesser than events that cause extreme increases in volatility. This could suggest that there are extraordinary news reports that result in extreme volatility changes. In light of this, positive extraordinary news reports have less influence on stock return volatility than negative extraordinary news reports of the same magnitude. On average, daily stock returns were greatly affected by large increases in volatility as a result of bad news reports (for example news report on the crash of the Wall Street). Another study for the UK was done by Soroka (2006) which explored asymmetries in mass media responsiveness to good and bad economic changes and public responsiveness to both the economy and economic news coverage. The findings from this study showed that media responses to economic conditions are asymmetric. This suggests that the media is biased towards publishing more negative economic news than positive economic news. Furthermore, it could also be the reason why bad news has a greater impact than good news, because the markets are constantly receiving negative news in vast amounts, thus distorting investor perception about the market. These findings conform to the theory that asymmetries in good and bad news exist and also comply with other studies (see Boyd *et al.*, 2005; Dulwich, 2006) suggesting these asymmetries are as a result of the bad news. In contrast to this theory, Birz and Lott (2011) conducted a study for the US and found that positive news on GDP and unemployment had more impact on stock returns than negative GDP and unemployment news respectively.

The above empirical event studies provide evidence that news has an impact on stock markets and that bad news have more impact than positive news of the same magnitude. The following sections focus on empirical studies that employed the error term as the indicator of good and bad news.

3.2 Developed Economies

Dekpen (2001) conducted an extension of Lamoureux and Lastrapes's (1990) study that employed daily trading volume as a proxy for information flow in explaining the persistence of volatility shocks. Dekpen (2001) replaced the proxy for information flow (daily trading volume) with a decomposition of volume that proxies as a proportional measure of bad news and good news entering the market. Information flows that occur while the market is closed were excluded.

Findings from this study showed that volatility persistence was above 0.7 which suggests that the conditional volatility of the previous period has an impact on volatility in the current period. The persistence in variance explained by the decomposed information flows was greater than when using the aggregate measure of information flows. Furthermore, the variance of younger stocks was found to react asymmetrically to good news whereas older stocks reacted symmetrically to the type of information received by the market. The results were in contrast to the findings of other researchers (Boyd *et al.*, 2005 and Dulwich, 2006) where stock return reacted asymmetrically to bad news. Dekpen (2001) argued that the findings showed incomplete formulated expectations by the market on the firm's ability to provide positive returns in the future.

Blasco *et al.* (2002) conducted a study for Spain and used a direct test of the impact of published economic news on stock volatility. The main focus of the paper was to test whether the asymmetric response of volatility can be due to the effects of bad news. The paper employed daily closing prices of the Ibex35 index in the Madrid Stock Exchange. In respect to news, the paper focused on news that was considered of general interest for investors (for example, joining the EU, unemployment reports and consumer price index).

Blasco *et al.* (2002) presented this study in two stages: the first stage included models with a complete set of news ranked into groups by relevance and the second stage showed daily information showing only one sign for each day as a reference of what occurred during trading sessions thus meaning that three different possibilities were assigned each day (i.e. good news, no news and bad news). A GARCH model and a GJR (Glosten-Jagannathan-Runkle) model were incorporated in this study. A GJR model was employed because it was argued that it permitted the inclusion of an exogenous variable that allowed different responses depending on the sign of the news entering the market (Blasco *et al.*, 2002).

With regards to findings from the first stage, this study showed that good news increased returns and bad news decreased returns while the GARCH model shows that both good and bad news increased the level of volatility (Blasco *et al.*, 2002). The findings from the second stage showed that bad news was significant, thus cementing the theory that an asymmetric response of volatility was a result of the bad news. The argument for the difference in results was due to the use of different information in each case.

Blasco *et al.* (2005) conducted another study on stock returns in Spain which attempted to analyse the kind of information that affected the close-to-open returns, open-to-close returns, volatility and volume in actively traded individual securities. The data employed consisted of daily opening and closing stock prices, volume of the Ibex35 and eleven large individual securities. The period taken into account for this study was from January 1997 to March 1999. The GARCH and EGARCH models were used in this study. The findings revealed that good news was significant in the mean equation and bad news in the conditional variance. Bad news was found to increase current volatility (Blasco *et al.*, 2005). These findings show continued support for other studies by Boyd *et al.* (2005), Chen *et al.* (2003), Dulwich, (2006), Blasco *et al.* (2002) and Liau and Yang (2008) that asymmetric response of volatility is caused by bad news.

Shi *et al.* (2015) conducted a more recent study on US data that analysed the impact of news sentiments across industries in different macroeconomic states. Using the Markov Regime-Switching-GARCH, Shi *et al.* (2015) found that the effect of good news on stock return volatility was greater in a state of economic calm than in a turbulent state. Furthermore, it was discovered that in a state of economic calm, the energy, material, utilities and industrial sectors showed that bad news had a greater effect on stock return volatility relative to other sectors. The effect of both good and bad news was found to be the same in the health care and consumer staples sector. The defensive nature of these two sectors might be the reason for the symmetrical impact of the good and bad news. Bad news had a greater impact on volatility in the IT sector. Shi *et al.* (2015) argued that some sectors receive less news flow relative to other sectors, thus implying that the marginal effect of each news release on return volatility is higher in companies belonging to sectors that have lower news flow.

In summation, the reviewed literature showed that most studies were conducted for the USA and the results found were in support of the theory that bad news (negative news) had a significant impact on stock return volatility than the good news of the same magnitude. It can also be noted that different methodologies were employed in different studies but the results emanating from those studies were the same. Another aspect that can be observed was that the impact of good and bad news of stock return volatility varies across different economic sectors.

3.3 Developing Economies

This section analyses the empirical evidence of the impact of good and bad news on return volatility in developing or emerging economies. Equities traded in the developing capital markets tend to have different characteristics than those traded in developed countries. According to Aggarwal *et al.* (1999), emerging markets equities exhibit distinguishing features from those traded in developed markets, such as low correlations with developed markets, high sample average returns, high volatility and more predictable return patterns. In this regard, it is worthwhile to review existing studies within emerging markets.

Henry (1998) conducted a study for Hong Kong that modelled the asymmetry of stock market volatility. This study followed Engle and Ng (1993) by employing the error term (ε_t) as a collective measure of news. Bad news is when there is an unexpected decrease in returns ($\varepsilon_t < 0$), and good news ($\varepsilon_t > 0$) is when there is an unexpected increase in returns. Data consisted of daily closing values of the Hang Seng Index transformed into continuously compounded returns. In order to take into account the day of the week effect, the rate of return was initially regressed on a constant and four day-of-the week dummy variables and the residuals were also included (Henry, 1998). The study also incorporated the GARCH, GJR, EGARCH and GQARCH models and after all the diagnostic checks the GQARCH model was found to be suitable. Henry (1998) found that news impact of the Hong Kong stock market is asymmetric with bad news having more impact on stock return volatility than good news. Furthermore, shocks to volatility were found to be infinitely persistence. This suggests that the previous period conditional volatility explains the current period conditional volatility.

Another study for India by Sinha (2006) focused mainly on modelling the phenomenon of volatility clustering and persistence of shock using asymmetric GARCH models. The study consisted of data obtained covered a ten-year period from March 1995-March 2005. Sinha

(2006) argued that this period marked a major transformation in the structure and functioning of the Indian stock market. In contrast to Henry (1998), daily opening, high, low and closing stock price data for the Sensitive index (related to the Bombay stock exchange) and Nifty (related to the National stock exchange) was employed. These market indices were argued to be a fairly representative of various industry sectors. Sinha (2006) incorporated the EGARCH and GJR-GARCH models to explain the conditional variances in the returns. The EGARCH model was a perfect model to explain the asymmetry in the Sensitive index whereas the GJR-GARCH was better at explaining the asymmetry in the Nifty case.

Findings from this study showed that Sensitive index and Nifty were asymmetric with bad news having more impact on the stock return volatility than positive news. The shocks in volatility were also found to be persistent suggesting that previous period shock may take a long time to die out. These findings support the study by Henry (1998).

Banumathy and Azhagaiah (2015) employed both symmetric and asymmetric GARCH models to examine stock market volatility in India. Their findings showed that leverage effects exist in the Indian stock market and also that negative shocks had a greater effect on the stock return volatility than positive shocks. Another study for India by Sinha (2015) focused on stock price volatility with reference to the automobile sector. Findings from employing a TGARCH model showed that leverage effects were present in the automobile sector and also that negative shocks had a greater impact on stock return volatility than positive shocks of the same magnitude.

Using both symmetric and asymmetric models, Abdalla and Winker (2012) conducted a study on two African exchanges, Sudan's Khartoum stock exchange (KSE) and Egypt's Cairo and Alexandria stock exchange (CASE). The main objective of this study was to model stock return volatility in two African markets by using different univariate GARCH models. Similarly to Suleman (2012), Henry (1998), and Barunik *et al.* (2015) daily closing prices were incorporated. Furthermore, Abdalla and Winker (2012) calculated the daily returns as the continuously compounded returns as was done by Henry (1998). Univariate GARCH models employed to model symmetric and asymmetric volatility included GARCH (1, 1), GARCH-M (1, 1), TGARCH (1, 1), PGARCH (1, 1) and EGARCH (1, 1) (Abdalla and Winker, 2012). It was also highlighted that due to the decline in the KSE over the study period, the data set was divided into sub-periods, and therefore a dummy variable was introduced in the mean equation.

Findings from the GARCH (1, 1) model employed indicated that the conditional volatility of stock returns on the KSE are explosive whereas the CASE index was persistent. The CASE findings correspond to those for other developing economies (see Sinha, 2015; Henry, 1998). A GARCH-M model showed that there was a positive risk premium in both stock markets which suggests that it is consistent with a theory which states that a higher the risk level, the higher the expected return on assets. The EGARCH and TGARCH models that are suited for investigating the presence of leverage effects showed that in both the KSE and the CASE, the stock return volatility was asymmetric. Negative shocks (bad news) have a larger impact on conditional volatility than positive shocks (good news) of the same magnitude (Abdalla and Winker, 2012). Similar findings to those of EGARCH AND TGARCH were discovered in the Power GARCH (1, 1) in the case of Egypt.

A study for Lebanon by Bouri and Salloum (2015), focused on modelling the second moment of the Lebanese stock market. Modelling the second moment for asset returns was argued to be important for portfolio maximisation, asset pricing and risk management (Bouri and Salloum, 2015). Daily closing prices of the Blom equity index[1] were used to model stock return volatility, the EGARCH model was found to be the most appropriate model. The argument for employing the EGARCH was that it allows for asymmetric response in conditional variance. Findings from this study showed that in the Lebanese stock market, bad news causes lower volatility than good news. The argument for this negative association between volatility and negative shocks was attributed to the fact that investors in Lebanon are more sensitive to good news than bad news. This suggests that the Lebanese stock market provides investors with protection from negative shocks and also that good news had a greater impact on stock return volatility than bad news. These findings were congruent with a study by Birz and Lott (2011), which showed that positive

[1] The Blom equity index is a capitalisation-weighted index of all the listed companies in Lebanon used as a proxy for the performance of Lebanon sole exchange, the Beirut Stock Exchange.

news about GDP and unemployment had a greater impact on stock return volatility than bad news.

Liau and Yang (2008) studied the mean and volatility asymmetry of Asian stock markets using the ANST-GARCH (Asymmetric Non-linear Smooth Transition GARCH) model. It was argued that this model would be able to show more clearly whether investors react more strongly to bad news after a heavy loss (Liau and Yang, 2008). Daily closing prices of stock indexes were employed. The period of the study was from January 1994 to March 2005. According to Liau and Yang (2008), this period enabled them to look at the asymmetric mean reversion and volatility before the Asian financial crisis and after the crisis. The Asian countries that were included were Japan, Hong Kong, Thailand, Singapore, Taiwan, South Korea and Malaysia.

Findings from the descriptive statistics for the daily index return showed that the mean return for each market was negative except for Singapore, South Korea and Thailand. For Singapore, positive returns could be attributed to the robust financial system, diversified asset allocation or a stronger economy (Yelten, 2003). Volatility was higher in the post-crisis sub-period than the pre-crisis sub-period. Furthermore, Liau and Yang (2008) found that positive returns were persistent whilst negative returns showed a reversing trend for all markets except for South Korea and the asymmetric response of volatility to stock return shocks was evident in each market. Negative returns reversions were also found to be faster in the post-crisis sub-period thus implying that past bad news became influential in investor decision-making process.

Using the EGARCH model, Suleman (2012) tested the stock market reaction of the Pakistan stock exchange to good and bad political news. Good political news was found to have more impact in the automotive and parts sector and the financial sector compared to any other sector. Suleman (2012) also found that good political news reduced volatility in the KSE 100, utilities, food and beverage, basic materials, health care and industrial sectors. For the financial, Oil and gas sectors, good political news was found to have no effect on volatility. Furthermore, Suleman (2012) discovered that bad political news had more positive impact on volatility in the basic material and the financial sector when compared with other sectors. The health sector and industrial sector were the only exceptions. Similarly to studies done for developed countries, volatility asymmetry was negative and persistent in all sectors including the KSE 100.

Coffie (2015) modelled and forecast stock return using asymmetric model for both Ghana and Nigeria. Using daily stock price indices of the Ghanaian stock exchange all index (GSEI) and the Nigerian stock exchange all share index (NSEI) and employing the GJR GARCH and EGARCH, it was discovered that in both markets the impact of news was asymmetric. In Ghana, both the GJR and EGARCH models captured the leverage effects of the stock returns thus implying that negative news had a greater impact than the good news of the same magnitude. However, in Nigeria, the findings controverted the widely accepted observed theory of volatility asymmetry. Evidence showed that stock return volatilities reacted more to positive news than negative news. Coffie (2015) argued that such a finding could be as a result of investor behaviour. Nigerian investors are more responsive to momentum stocks (i.e. price rising stocks) resulting in higher trading volumes than the negative counterparts thus giving rise to volatility.

Ndwiga and Muriu (2016) studied stock return volatility in emerging equity markets using Kenya as a case study. Using the TGARCH and EGARCH models, no evidence of leverage effects was found on the Nairobi stock exchange (NSE). This implied that the impact of bad news and good news on stock return volatility was symmetrical. Ndwiga and Muriu (2016) argued that these findings were as a result of regulation and policies implemented to minimise market information symmetry. Similarly to Ndwiga and Muriu (2016), Aljafari (2012) findings showed no evidence of asymmetry in Muscat stock market which confirmed the absence of the leverage effects in the return series. This suggests that both good and bad news have a symmetrical impact on stock return volatility. It was also found that the volatility is highly persistent which suggests that news about volatility from the previous period helps to explain the current period volatility. Al-Najjar (2016) employed the ARCH and GARCH models in modelling and estimating the volatility of the Jordan stock market. Using daily closing prices of the Amman Stock Exchange and the EGARCH model to capture asymmetry Al-Najjar (2016) found no evidence of leverage effects in Jordan. This means that both good and bad news have the same impact on the future volatility.

3.3.1 South Africa

For South Africa, Mandimika and Chinzara (2012) focused on the nature of volatility, risk-return relationship and the long term trend of volatility on the equity markets. Data included daily closing indices of four JSE benchmark indices, nine industrial indices and thirty-three sectoral indices. Furthermore, one symmetrical and two asymmetrical GARCH-in-mean models were also included in this study. Using the TGARCH-in-mean model, findings showed that the South African stock market volatility was asymmetric and persistent. Mandimika and Chinzara (2012) went on to discover evidence of leverage effects in all sectors of the economy. No evidence of leverage effects was found in the automobile and parts sector. Real estate also showed no evidence of leverage effects.

This study does not only focus on modelling stock return volatility of different sectors but it also attempts to forge an understanding of the investor behaviour in various economic sectors brought about by their response to good and bad news filtering through the markets. Possible explanations will be provided if there are any variations in return volatility across sectors and the benchmark indices used. Despite the similarities in sectoral analysis covered by Mandimika and Chinzara (2012), this study employs only the asymmetric GARCH models (EGARCH and TGARCH) to capture the impact of good and bad news on stock return volatility. The other difference is that this study covers a longer period inclusive of the most recent data and a longer period post the 2007 global financial crisis. This means that different events (for example new regulation policies implemented) which are likely to have an impact on stock market returns during the course of the sample period will be reflected in the time series. Mandimika and Chinzara (2012) only analysed the behaviour of volatility but did not provide reasons why different sectors might behave differently. This study tries to bridge this gap by explaining why stock return volatility varies across sectors, as well as reasons why sectors behave symmetrically or asymmetrically to good and bad news.

Another study for South Africa by Arguile (2012) focused on the performance of defensive shares on the JSE during the financial crisis. Conditional volatilities of each sector was analysed by employing the GARCH model and two of its extensions, namely EGARCH and TGARCH models. Sector volatilities relative to the market for the entire sample period showed that the

Telecommunications, Technology and Oil and Gas sectors experienced the highest volatility whereas the Industrials, Consumer services and Financials sectors experienced the lowest levels of volatility. Arguile (2012) found evidence of leverage effects in all sectors except for healthcare for the whole sample period. Furthermore, during the financial crisis few sectors experienced leverage effects, namely Oil and Gas, Telecommunications, Basic materials, Consumer services and the All-share index.

Arguile (2012) also found that during the financial crisis the consumer services sector and financial sector showed evidence of increasing persistence whereas the healthcare, telecommunications, oil and gas and basic materials showed lower persistence respectively. These findings suggest that others sectors are defensive in nature thus are able to withstand a crisis whereas, others are cyclical industries in nature (for example financials and consumer services) thus cannot withstand a crisis. Using EGARCH and TGARCH models, Niyitegeka and Tewari (2013) found no evidence of asymmetric effects of news on conditional volatility on the JSE whereas volatility of stock returns was found to be persistent.

To understand the type of news that affect each sector, Chinzara (2011) conducted a study that focused on macroeconomic uncertainty and stock market volatility. Monthly stock market indices for four sectors, namely Mining, Industrial, Financial, the General retail and the overall market ALSI index were employed. The data included the following macroeconomic variables: broad money supply, industrial production, headline consumer price index, oil price, gold price and treasury bills rate (short-term interest rate).

Using a VAR and EGARCH models, Chinzara (2011) found that information about short-term interest rates, oil price, exchange rate and gold price had a greater impact on stock market volatility relative to broad money supply, industrial production and headline consumer price index. Amongst all the above-mentioned variables, the short-term interest rate was dominant in explaining the volatility on the ALSI, retail sector and the industrial sector whilst the exchange rate dominated in the financials and mining sectors. Chinzara (2011) argued that the Financials sector was exposed to the exchange rate because of foreign exchange activities of banks, thus making their earnings volatile. Mining sectors are heavily involved in export, thus exchange rate volatility will also influence their earnings. Evidence of asymmetry and volatility persistence was found in all four sectors thus implying that negative news had a greater impact on stock return volatility than positive news of the same magnitude.

Using TGARCH, GARCH-in MEAN and EGARCH, Makhwiting *et al.* (2012) developed the ARMA GARCH type models for modelling volatility and financial market risk of share on the Johannesburg stock exchange. It was found that the impact of news is asymmetric with the bad news having more impact than the good news of the same magnitude. This was in line with negative skewness of the return series. Leverage effects were also found to exist and bad news indeed increased volatility more than good news. Volatility shocks on stock returns were highly persistent meaning that it takes a while for them to die out.

3.4 Conclusion

The literature reviewed on developed economies showed mixed findings with regards to asymmetry responses of stock return volatility to good and bad news. However, many studies supported the theory that negative news has a greater impact on stock return volatility than good news. Most findings in developing countries were similar to developed countries with regards to the presence of leverage effects and volatility persistence. They also conformed to the theory that negative news has a greater impact on stock return volatility compared to positive news of the same magnitude. This suggests that asymmetry in stock return volatility is as a result of the bad (negative) news. Contradictions to developed countries findings were also present in some studies for developing countries where it was discovered that no leverage effects or asymmetry existed. A possible explanation for such findings would be the policies put in place by governments which shield investors from the implications of good and bad news. For this reason, reviewing the literature on South Africa was important so as to observe how its equity market responded to the good and bad news.

The reviewed literature for South Africa showed that most sectors exhibit evidence of asymmetry, with negative news having a greater impact on stock return volatility than positive news. Volatility persistence was also found to be present in all sectoral stock returns. It was also evident that such findings are congruent with most of the reviewed literature from both developed and developing countries. With regards to studies that focused on specific sectors, their findings showed that some sectors are defensive in nature, thus exhibit for example, the Health care sector and thus they exhibit lower stock return volatility. Other sectors were found to show high stock return volatility, for example, the Financials and Consumer services sectors. This suggests that the impact of news whether positive or negative differs for each sector. This implies that the study of the impact of good and bad news on sectoral stock returns volatility is important in aiding investors to make informed decisions and to minimise risk.

CHAPTER 4. DATA AND METHODOLOGY

4.1 Introduction

This chapter focuses on the analytical framework employed to achieve the objectives listed in Chapter One. Issues with regards to data used and the properties of the data are also discussed. Following other empirical studies (Blasco *et al.*, 2005; Mandimika and Chinzara, 2012; Chinzara, 2011; Chinzara and Aziakpono, 2009; Mandimika, 2010; Suleman, 2012), asymmetric GARCH models, in particular the Exponential-GARCH (EGARCH) by Nelson (1991) and Threshold-GARCH (TGARCH) by Zakoian (1993), are used to analyse the conditional volatilities and capture any asymmetric effects.

The rest of the chapter is organised as follows. Section 4.2 discusses the data employed in this study. Section 4.3 examines the TGARCH and EGARCH specifications used in modelling stock return volatility of the sectoral indices. Section 4.3 also covers the diagnostic checks that should be done to assess if the chosen model is a good fit and captures all the dynamic aspects of the mean and conditional variance models. Section 4.4 provides a summary of the chapter.

4.2 Data

4.2.1 Sources and Properties of data

The selected sectors in this study are provided in Appendix A (Table A1). The selected period of study was based on the availability of data. The Industrial Classification Benchmark (ICB)[2] was also used for selection of South Africa's equity market sector indices. According to Syriopoulos *et al.* (2015), sectoral indices provide useful information that market players employ to form investment strategies and evaluate portfolio allocation decisions.

[2] The ICB is a system categorizing over 70000 companies and 75000 securities worldwide. It is supported by the ICB database and comprises data for global sector analysis and is maintained by the FTSE International.

Daily data were obtained from Thompson Reuters Eikon for a sample period covering 2 January 1997 to 17 August 2016 for all sectors except the Oil and Gas, small-cap and mid-cap. The start date for the analysis of the study was chosen due to the availability of data. The Oil and Gas sample was restricted up to 30 June 2015. The reason for this was because of the rebasing that was done in July of that year. According to Vendeiro (2015), the FTSE/JSE oil and Gas index was rebased by dividing the closing index value by 10, causing the index values to be ten times lower than the previous day closing values. The problem with rebasing the data is that important information will be thrown away. Small-cap and mid-cap samples only started on the 2nd of June 2002. This data consists of daily closing prices of three benchmark indices and nine sectoral indices of the JSE. In this study, the reasoning for using daily data was that a better reflection of South Africa's stock market reaction to news entering the market can be observed since the information is adopted and incorporated quickly into asset prices.

In addition, the sample will be split into three periods namely, pre-crisis, during crisis and post-crisis. The official dates of the 2008 global financial crisis were obtained from the South African Reserve Bank (SARB) website. SARB identified the beginning of the crisis as December 2007 and ending towards the end of August 2009. Since the stock market is one of the leading indicators of the business cycle (Goodspeed, 2013), the downturn in the stock market is used to ensure a more accurate representation of the financial crisis. The peak in the stock market cycle indicated by the ALSI on 11 October 2007 will represent the start of the downturn (i.e. start of the 2008 global financial crisis) and 03 March 2009 marks the end of the downturn (i.e. end of the global crisis).

The overall sample level series graphs in Appendix B1 show that the price series of all the sectors and benchmark indices follow a random walk process. The price series tend to deviate further away from the mean over time, implying that the series are non-stationary. Appendix B2 shows the return series of all sectors and benchmark indices for the pre-global financial crisis, during-global financial crisis, post-global financial crisis periods and the overall sample period hovering around the mean, which could suggest that the series might be stationary. Stationarity tests will be conducted to identify if the return series are stationary or not.

According to Arguile (2012) distortions arising from non-trading days is one of the problems linked with using daily data. Following Chinzara and Aziakpono (2009), Chinzara (2011); Mandimika and Chinzara (2012) non-trading days-which include weekends and holidays-were excluded from the data. As is practice in standard empirical literature (Alberg *et al.*, 2008; Chinzara, 2011; Henry, 1998 and Mandimika and Chinzara, 2012), the daily stock prices will be converted to continuous compounded returns as follows:

$$y_t = (ln\, P_t - ln\, P_{t-1}) \times 100 \qquad (1)$$

where y_t represents the daily returns continuously compounded, *ln* is the natural logarithm, P_t represents the closing price index and P_{t-1} is the previous day closing price index.

4.2.2 Descriptive statistics

Appendix A (Tables A3.1 to A3.4) provide descriptive statistics of the data for the overall sample, pre-crisis, during-crisis and post-crisis periods. The reported descriptive statistics include the sample mean, median, maximum, minimum, skewness, kurtosis, Jarque-Bera statistic and standard deviation. The main purpose of including these is to check the distributional properties of the returns series (Kgosietsile, 2014).

4.2.2a Whole sample period

For the whole sample, it is evident that all the mean returns are positive and several sector returns were found to outperform the overall market over the period analysed. These sectors include Consumer goods, Consumer services, Health care, Oil and Gas, Industrials and Telecommunications with average daily returns ranging from 0.045% to 0.067%, which was above the All-share average of 0.044%. The highest daily average returns were for Consumer goods (0.067%) followed by the Oil and Gas sector (0.062%) and lowest daily returns were recorded for the Technology sector (0.018%).

The standard deviation of returns shows that the Telecommunications sector (2.12%) has the highest volatility with respect to all the other sectors included in this study. The Oil and Gas sector (2.05%) recorded the second highest standard deviation. This is congruent with the risk-return relationship, which states that the higher the return, the more risk involved. The high standard deviation in these sectors can partially be explained by the global financial crisis. Appendix A (Table A3.1) shows that the Telecommunications (2.12%) and Oil and Gas (2.05%) sectors are more volatile than any other sectors. Industrials (1.25%) had the lowest standard deviation followed by Consumer services (1.28%). The results with regards to standard deviation shown in Table A3.1 (Appendix A) also show that all the sectors except for Industrials are more volatile than the All-share index.

The maximum return value of 31.08% was recorded in the Oil and Gas sector whereas the minimum return value of -20.8% was recorded in the Technology sector. The Consumer services sector had the lowest minimum value of -10.37% and a maximum of 7.5% suggesting that this sector is not highly volatile when compared to other sectors.

The descriptive data shows the characteristics that are common in financial series. For example, the Jarque-Bera test statistic for normality indicates that in all sectors the null hypothesis that returns are normally distributed was rejected at the 1% level of significance. Support of non-normality was confirmed by skewness and kurtosis. All the sectors and the benchmark indices except for Oil and Gas show that the returns are negatively skewed, suggesting that return distributions are asymmetric. Mandimika and Chinzara (2012) state that negatively skewed returns imply that the return distribution of both sectors and indices is likely to earn returns above the mean. The Oil and Gas sector is positively skewed, suggesting that the impact of good news may be greater than that of bad news of the same magnitude.

4.2.2b Pre-crisis period

During the pre-crisis period in Table A3.2 (Appendix A), Telecommunications, Oil and Gas, Basic materials and Consumer goods recorded the highest positive mean returns respectively. The Technology sector had a negative mean return which could be because of the ripple effects from the internet bubble crisis in the early 2000s. The Small-cap and Mid-cap respectively outperformed all the sectors with high returns of 0.11% and 0.09%. The Technology, Telecommunications and Consumer goods sectors recorded the highest standard deviation and with Consumer services and Industrials recording the lowest standard deviation. All the benchmark indices were less volatile than all the sectors. The results for this period also showed that all sectoral returns, except for Consumer goods, are negatively skewed and are not normally distributed.

4.2.2c During-crisis period

Negative mean returns during the financial crisis period were recorded for Basic materials, Oil and Gas, Industrials, Financials and Technology respectively. Other sectors such as Health care, Consumer services and Consumer goods had positive returns. A possible explanation for such positive returns could be attributed to the defensive nature of these sectors (see, Arguile, 2012). The most volatile sectors during this crisis period was found to be Basic materials (3.30%), Telecommunications (3.08%), Oil and Gas (3.08%), Technology (2.39%) and Financials (2.01%). One would expect the Financials sector to be the most volatile, however this is not the case. A possible explanation could be the rigorous policies that were put in place by the monetary policy committee which enabled the Financials sector to be resilient to the global shocks. According to the National Treasury (2011), the policies that enabled the Financials sector to withstand the global crisis include limited exposure to foreign assets, a sound framework of financial regulation and well-regulated institutions, reduction of household vulnerability and countercyclical monetary policy.

A plausible explanation for such high volatility in the Basic materials sector could be the slow-down in the subsectors included in this sector namely, mining, platinum and precious metals and general mining. South Africa is a large exporter of minerals and due to the global financial crisis global markets came to a halt and the demand for South Africa's exports fell. According to Baxter (2009), the global recession resulted in the decline in mineral exports demand, a decrease in the availability of funds, lower revenues and higher production costs in the mining sector.

The least volatile sectors were Consumer services, Industrials and Health care respectively. According to Goodspeed (2013), during bearish periods (such as the crisis) these sectors become more attractive for investors because consumers still need basic goods such as food and medication whatever the state of the economy. For this reason, it can be argued that investors in these sectors were more optimistic which led to low volatility being experienced.

4.2.2d Post-crisis period

Appendix A (Table A3.4) shows that for this period Consumer services, Health care, Technology, Consumer goods and Oil and Gas have positive mean returns. The Basic materials sector recorded a negative mean return which could be as a result of the slump in the commodity prices causing the stocks in this sector. Telecommunications, Industrials, Financials and all benchmark indices recorded a low mean return. The highest standard deviation was recorded in Oil and gas (2.09%), Telecommunications (1.71%) and Basic materials (1.56%) sectors. The least volatile sectors were Industrials (1.01%), Financials (1.04%), Consumer goods (1.09%) and Health care (1.10%). The main cause for the higher deviation in the Oil and Gas sector could be because of the sharp decline in the price of oil as a result of increased supply in the US and reduced global demand (Hou *et al.*, 2015). The sharp fall in the price of oil would drive down the profits earned by firms resulting in low returns. South African producers of petroleum experienced huge losses from this drop in prices. For this reason, lower returns experienced by investors may result in disposal of such stocks in their portfolios causing the volatility to surge even further.

In the Telecommunications sector, such large volatility would most likely have been triggered by the depreciation of the rand (Malan, 2016). The Telecommunications sector in South Africa uses mostly imported technology and the weakening of the rand makes the technology more expensive. Expensive technology coupled with the low supply of relevant ICT skills will result in high operating costs for firms in this sector which will drive up the prices, thereby reducing profits made and increasing return volatility. The high deviation recorded in the Basic material sector would have increased partly due to the subsectors that make up this sector (for example the mining industries). According to the Mining Review (2015) labour actions, increased cost pressures and the decline in commodity prices have resulted in shrinking profit margins. In this regard, higher operation costs and lower profits will likely cause the return volatility to increase.

Volatility experienced in the Financials and Basic materials sector can partially be explained by the firing of the Minister of Finance towards the end of 2015 for political reasons. Suleman (2012) found that bad political news has more impact in the Basic material and Financials sectors compared to other sectors. According to Bloomberg (2015), as a result of this incident the rand plummeted against the US dollar and the banking sector also experienced significant declines. A weaker rand would mean a rise in the risk of bad debts, and an increased probability of South Africa's credit ratings declining to junk status thereby increasing the cost of borrowing. Ultimately, investor confidence is lost and a higher stock return volatility is inevitable in all these sectors.

All the benchmark indices were less volatile than all the sectors. With regards to skewness, mixed findings can be observed in Table A3.4 in Appendix A. Some sectors, namely Financials, Industrials, Consumer services, Telecommunications and Health care are negatively skewed whereas Basic materials, Consumer goods, Technology and Oil and Gas are positively skewed.

4.3 Method

4.3.1 Stationarity tests

Brooks (2008) defines a stationary time series as one with a constant mean and variance over a period of time. A stationary time series also has constant auto-covariance (Enders, 2010). Data that is stationary is important because it reduces the likelihood of the regression being spurious and allows for forecasting. According to Enders (2010), non-stationary data may have a pronounced trend or meander without a constant mean or variance. This means that a shock to the system will have infinite persistence over a period of time. Empirical findings will be of little value if non-stationary data is used.

Informed by Mandimika and Chinzara (2012), this study will perform two tests for stationarity, namely, the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. According to Brooks (2008), the null hypothesis for the ADF is that the series has a unit root. If the ADF observed tau-statistic values exceed critical values, then the null hypothesis is rejected indicating that the series has no unit root and thus it is stationary. If the observed tau-statistic value is less than the ADF tau-critical value then the series is non-stationary (i.e. it has a unit root).

The KPSS differs from other unit root tests in that the series is assumed to be stationary under the null hypothesis (Kwiatkowski *et al.*, 1992). The use of both the ADF and the KPSS testing is known as confirmatory data analysis (Brooks, 2008). This means that these two tests should come to the same conclusion for them to be robust. If different conclusions are obtained for the two tests, the KPSS results would then be preferred to the ADF results.

4.3.2 Analysis of volatility

Financial data is characterised by leverage effects, volatility mean reversion, fat tails and volatility clustering and, hence, according to Brooks (2008) the use of linear structural models cannot adequately capture these properties. The stylised features of financial time series suggest that the error term variance is not constant. According to Bakry (2006), literature on stock market volatility has progressed significantly in terms of the complexity of methods used to model volatility. More advanced econometric techniques based on modelling conditional variance have replaced the basic standard deviation as a volatility measure.

In light of this, Autoregressive Conditional Heteroscedasticity (ARCH) (Engle, 1982) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) (Bollerslev, 1990) models were first identified as the most suitable to capture these stylised features, as they are able to capture periods of both tranquillity and volatility in a time series. Of these two (ARCH and GARCH) models, the GARCH is the most widely used in practice. Brooks (2008) argues that GARCH models are preferred to ARCH models because they allow for the conditional variance to be dependent upon previous own lags, are more parsimonious, avoid over fitting and are less likely to breach non-negativity constraints.

Literature shows that stock return volatility is directly related to the flow of information to the market and financial leverage (Bakry, 2006). The information received by the market may be either positive or negative causing the prices to deviate from fundamental valuations. Extensive evidence (Abdalla and Winker, 2012; Dekpen, 2001; Henry, 1998) shows that stock return volatility is often asymmetrical. This asymmetry is argued to be a result of leverage effects, whereby a lower share price causes an increase in a firm's debt-to-equity ratio, increasing risk and leaving shareholders uncertain about future cash flows (Brooks, 2008). In this regard, a suggestion can be made that the impact of good news and bad news on stock return volatility is not symmetrical. With the GARCH model enforcing a symmetrical response of volatility to positive and negative shocks and failing to capture leverage effects, Brooks (2008) suggests that more advanced econometric models that capture this asymmetry should be incorporated in this study.

Given the weaknesses of the symmetric GARCH model and informed by previous empirical studies (Blasco *et al.*, 2005; Chinzara and Aziakpono, 2009; Chinzara, 2011; Mandimika, 2010; Mandimika and Chinzara, 2012; Suleman, 2012), asymmetric univariate GARCH models, in particular the Exponential-GARCH (EGARCH) proposed by Nelson (1991) and Threshold-GARCH (TGARCH) proposed by Zakoian (1993) and Glosten *et al.* (1993) will be employed to capture the potential asymmetric impact. According to Enders (2010), the EGARCH and TGARCH models allow for shocks to have different effects on volatility. This means that the different effects of good news (positive shocks) and bad news (negative shocks) of similar magnitude on stock return volatility for each sector can now be captured.

4.3.2a The mean equation

The first step in the analysis is to find the appropriate mean equation. According to Chinzara and Aziakpono (2009), the mean equation can take the form of a standard structural model, an autoregressive (AR) model or a combination of the two. In this study, a standard structural model is employed first since the aim is to generate a conditional variance series for each of the selected sectoral indices. The appropriate mean equation should be 'white noise' meaning that it should have a constant mean, variance and auto-covariance. Similar to Chinzara and Aziakpono (2009), Takaendesa *et al.* (2006), Mandimika (2010) and Arguile (2012), this study employs the following mean equations:

$y_t = \mu + \varepsilon_t$ *(2)*

$y_t = \mu + \sum_{i=0}^{p} \alpha_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} + \varepsilon_t$ *(3)*

where y_t represents the daily closing return of each sectoral index, μ is a constant and ε_t is the white noise error term. Autocorrelation tests will be performed using the Breusch-Pagan Godfrey serial correlation LM test. If autocorrelation is present in equation *(2)* an appropriate form of equation *(3)* will be employed.

4.3.2b Testing for ARCH effects

Prior to estimating the conditional volatility models, there is a need to test for ARCH effects in the mean equation. The reasoning behind testing for ARCH effects is that in financial time series, the magnitude of residuals appears to be related to the magnitude of recent residuals. According to Brooks (2008), ignoring ARCH effects may result in the loss of efficiency. To test for ARCH effects, the ARCH LM test is used. Testing for ARCH effects involves regressing the squared residuals on a constant and the lagged squared residuals up to lag q (Brooks, 2008). The null hypothesis is that of no ARCH effects and follows a Chi-squared distribution. If the value of the test statistic observed is statistically significant and greater than the critical values, then the null hypothesis is rejected and it is concluded that there is evidence of ARCH effects. This implies that a GARCH model would be appropriate to model the conditional volatility.

4.3.2c Asymmetric GARCH models

The TGARCH model is a simple re-specification of the symmetric GARCH, with an additional term added to take possible asymmetries into account (Brooks, 2008). This model allows for good news and bad news to have different effects on stock return volatility. The TGARCH has the mean equations *(2)* or *(3)* specified in section 4.3.2a, with the variance equation as follows:

$h_t = \Omega + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ *(4)*

where d_{t-1} is a dummy variable that is equal to 1 if $\varepsilon_{t-1} < 0$, and equal to 0 if $\varepsilon_{t-1} \geq 0$. Note that d_{t-1} also represents the asymmetry component and λ_1 is the asymmetry coefficient. In this model, good news ($\varepsilon_{t-1} \geq 0$) will have an impact of α_1, while bad news ($\varepsilon_{t-1} < 0$) will have an impact of ($\alpha_1 + \lambda_1$). Negative shocks are expected to have larger effects on volatility than positive shocks (Brooks, 2008; Enders, 2010). If $\lambda \neq 0$, the impact of news is asymmetric. In order to ensure that the non-negativity constraint is not violated, $\alpha_1 > 0$, $\beta \geq 0$ and $\alpha_1 + \lambda > 0$. Lastly, to ensure that the TGARCH model is stable, $\alpha_1 + \beta < 1$.

Another model that allows the capturing of the asymmetric effect of news is the exponential-GARCH (EGARCH). This model was developed due to the limitations of the pure GARCH (including the TGARCH) specifications, such as the possibility of violating the non-negativity constraint. According to Enders (2010), the EGARCH model has a logarithmic functional form which does not impose the non-negativity constraint on the model parameters. Enders (2010) note that the EGARCH model uses the level of standardised values of ε_{t-1} which allows for a more natural interpretation of the size and persistence of shocks. The EGARCH has the mean equation as specified in equations *(2)* or *(3)* in section 4.3.2a with the conditional variance equation as follows:

$$\ln(h_t) = \Omega + \gamma(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \alpha_1[(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - \sqrt{2}/\pi] + \beta_1 \ln(h_{t-1}) \qquad (5)$$

where α_1 is the coefficient of the lagged residuals and β_1 is the coefficient of the lagged conditional variance. γ is the asymmetric coefficient and Ω is the intercept term. The stability condition of the EGARCH model is where $\alpha_1 + \beta_1 < 1$ and if $\gamma < 0$ and statistically significant, volatility will be asymmetric with negative shocks having a greater impact on the conditional variance in the next period when compared to positive shocks of the same magnitude (Chinzara and Aziakpono, 2009).

4.3.2d Diagnostic Checks

Following estimation of the various asymmetry models, diagnostic checks should be performed in order to test that there are no ARCH effects remaining. According to Enders (2010), the estimated residuals of the mean equation should not display any form of serial correlation or conditional volatility. The ARCH-LM test will be employed for this purpose because it is relatively simple to conduct and does not require estimation of the full model. If serial correlation continues to exist then the model is not correctly specified because they are neglected GARCH effects in the residuals (Enders, 2010; Mandimika, 2010). This then implies that some trial and error is necessary to obtain the most appropriate model of the conditional variance. If no ARCH effects are found, this suggests that standardised squared residuals are no longer correlated and there is no remaining conditional volatility. This also means that future forecasts can now be made for the mean and conditional variance.

4.4 Summary

This chapter focused on the method and data employed in this study. Firstly, the sources and properties of data were discussed. Selected sectors were based on the ICB classification and the sample period was influenced by the availability of data. From a visual observation of the data, the price series deviated from the mean suggesting that they are not stationary, while the compounded return series indicated the properties of financial data such as volatility clustering and volatility mean reversion. The return series was hovering around the mean suggesting the possibility of stationarity.

The descriptive statistics for each sector in the sub-sample periods and whole sample displayed the common characteristics of financial data such as non-normality. It is also interesting to note that in the overall sample, the standard deviations in the Telecommunications and Oil and Gas sectors were partially explained by the global financial crisis. In addition, some sectors such as the Consumer goods, Consumer services and Health care experienced positive mean returns during the crisis, suggesting that means that they are defensive in nature.

A description of the econometric methods followed. This section comprised the stationarity tests and volatility analysis to be used. To model the stock return volatility an appropriate mean equation is estimated following a series of trial and error. Once this is done, the next stage is to determine the econometric models that can capture the asymmetric impact of good and bad news. ARCH effects are tested and if found to be present implies that the mean equation does not adequately capture all the conditional volatility, thus asymmetric GARCH models would be appropriate. The TGARCH and EGARCH are more suitable models for this study because they were not only extensively used in existing literature but also allow for the news impact to have a different impact on stock return volatility. Lastly, the ARCH-LM test is used to carry out the diagnostic checks because of its simplicity to conduct. The next chapter presents and the analyses of findings.

CHAPTER 5. RESULTS AND DISCUSSION

5.1 Introduction

The previous chapters provided a theoretical foundation and overview of the literature against which the analysis of this study is conducted. The purpose of this chapter is to report the results obtained from the tested hypothesis that the impact of good and bad news is asymmetric and impacts differently on different stock market sectoral indices. The chapter is organised as follows: Section 5.2 reports the stationarity test results, while Section 5.3 reports the asymmetric GARCH results of the sub-samples and the whole sample. Section 5.4 reports and provides an analysis of the differential impact of good and bad news. Section 5.5 provides a summary of the chapter.

5.2 Stationarity Tests

Stationarity tests for all the sub-samples and the overall sample are reported in Appendix A (Table A2). The results from the ADF test for all sectors show that the observed t-statistic is significant, therefore the null hypothesis of a unit root is rejected for all return series in level terms implying that the series of all sectors are stationary in level terms. The KPSS test also showed similar findings of stationarity in level terms for all sectors at the 1% level of significance. The observed LM statistics for all the sectors in sub-samples and overall sample are insignificant, therefore we fail to reject the null hypothesis of a stationary series. Since the return series are all stationary they can be used in further analyses.

5.3 Time series estimates of conditional volatility

5.3.1 Mean equation

The mean equation specified in Chapter 4 was estimated for each sector during each sub-period and the sample as a whole. Using the Box-Jenkins approach, all the mean equations followed an ARMA (p, q) structure as indicated in Appendix A (Tables A4.1 to A4.4). The most parsimonious model was chosen using the information criteria (AIC and SBC) given that such a model showed no sign of autocorrelation in the residuals. For the Consumer goods sector during the financial crisis period effort to find the correct ARMA structure were fruitless because of insignificant parameters, therefore this sector was estimated on a constant. Results for Breusch-Godfrey Serial Correlation LM test for autocorrelation are also shown in Appendix A (Tables A4.1 – A4.4). In all sectors and benchmark indices, the null hypothesis is not rejected and therefore there is no autocorrelation.

The next step was to test for the presence of ARCH effects in the mean equations to determine whether volatility is adequately captured or whether there is conditional volatility in the residuals. The ARCH-LM test was employed and the results are also reported in Appendix A (Tables A4.1 to A4.4) as well. All the sectors' test statistics (except for Consumer goods sector during the global financial crisis period) are statistically significant at the 1% level, which means that the null hypothesis of no ARCH effects can be rejected. This means that the mean equation does not capture the entire volatility in the series. The presence of ARCH effects suggests the estimation of the GARCH model will be appropriate, as GARCH models capture the time-varying conditional volatility of the estimated mean equations (see Mandimika and Chinzara, 2012; Frimpong and Oteng Abayie, 2006; Kovacic, 2008). The analysis of the asymmetry in the Consumer goods sector is not done for the global financial crisis period because there are no ARCH effects to capture or model.

5.3.2 Asymmetric GARCH Models

Table 1 to 4 presents the results of the TGARCH (*p, r, q*) model for all periods. The EGARCH model in Appendix A (Tables A5.1 to A5.5) show that $\alpha_1 + \beta_1 > 1$ or $\alpha_1 + \alpha_2 + \beta_1 > 1$ in all sample periods for most of the sectors and benchmark indices. The persistence in volatility of these sectors is explosive and the effect on the returns would have an infinite growth into the future Since the EGARCH model results for most of the sectors in all sample periods violates the stability condition they will be dropped from analysis and only those of the TGARCH model will be analysed.

In general, the TGARCH (1, 1, 1) is most widely used because it is more parsimonious (see Chinzara and Aziakpono, 2009; Arguile, 2012). However, due to the remaining presence of

GARCH effects and the failure to capture the volatility adequately in some sectors in preliminary analyses, in some instances the study employed higher order asymmetric GARCH models to eliminate the GARCH effects. For some sectors TGARCH (1, 1, 0) and TGARCH (2, 1, 0) are found to adequately capture the volatility in the return series.

Table 1: **Whole sample TGARCH (*p, r, q*)**

Sectors	Ω	α_1	β	λ	α_2	$\alpha_1 + \alpha_2 + \beta$
Basic materials	1.7610	0.1071	N/A	0.1778*	0.2530	0.3601+
Consumer goods	0.0280	0.0448	0.9136	0.0684*	N/A	0.9584
Consumer services	1.1662	0.1965	N/A	0.1776*	N/A	0.1965
Financials	0.0298	0.0574	0.8757	0.1039*	N/A	0.9331
Health Care	1.3319	0.2585	N/A	0.0584***	N/A	0.2585
Industrials	0.0400	0.0488	0.8745	0.1018*	N/A	0.9233
Technology	2.1804	0.3899	N/A	0.1817*	N/A	0.3899
Telecommunications	3.1291	0.2230	N/A	0.1623*	N/A	0.2230
Oil and Gas	2.6626	0.3676	N/A	-0.0720**	N/A	0.3676
Benchmark Indices						
All-share	0.0238	0.0391	0.8941	0.1031*	N/A	0.9332
Small Cap	0.2319	0.2425	N/A	0.1045*	N/A	0.2425
Mid Cap	0.0161	0.0485	0.8803	0.0803*	N/A	0.9288

Source: Authors' estimates

, **, * means that the coefficient is statistically significant at 1%, 5% and 10% level*

+, marks the summation of $\alpha_1 + \alpha_2 + \beta$ – which is a condition of stationarity of the GARCH model. For the sectors not marked by the (+) asterik, the condition for stationarity is $\alpha_1 + \beta$.

Table 2: **Pre-crisis sample TGARCH (*p,r,q*)**

Sectors	Ω	α_1	β	λ	$\alpha_1 + \beta$
Basic materials	1.9597	0.1735	n/a	0.1943*	0.1735
Consumer goods	0.0573	0.0611	0.8931	0.0686*	0.9542
Consumer services	0.0297	0.0640	0.8677	0.0894*	0.9316
Financials	1.1406	0.2639	n/a	0.2471*	0.2639
Health Care	1.4971	0.2364	n/a	0.1151*	0.2364
Industrials	0.0612	0.0585	0.8542	0.1037*	0.9127
Technology	2.9540	0.3317	n/a	0.1970*	0.3317
Telecommunications	3.2247	0.2473	n/a	0.1443*	0.2473
Oil and Gas	0.0571	0.0551	0.9081	0.0441*	0.9632
Benchmark indices					
All-share	0.0376	0.0553	0.8697	0.1067*	0.9250
Small Cap	0.0385	0.0440	0.7143	0.1873*	0.7583
Mid Cap	0.0456	0.0508	0.7622	0.1293*	0.8130

Source: Author's estimates

,,*** means that the coefficient is statistically significant at the 1%, 5% and 10% level*
Coefficients in italics are statistically insignificant
$\alpha_1 + \beta$- is a condition for stability for the univariate GARCH models

Table 3: **During-crisis sample TGARCH (*p,r,q*)**

Sectors	**Ω**	**α_1**	**β**	**λ**	**$\alpha_1 + \beta$**
Basic materials	8.7501	0.1527	n/a	*0.00581*	0.1527
Consumer goods	n/a	n/a	n/a	n/a	n/a
Consumer services	0.0377	0.0071	0.9230	0.1228**	0.9301
Financials	0.0481	0.0943	0.8624	*0.0781*	0.9567
Health Care	0.5492	0.0962	0.6777	*0.0932*	0.7739
Industrials	2.4398	*0.1102*	n/a	*-0.0080*	*0.1102*
Technology	0.2130	0.1056	0.84572	*0.0249*	0.9513
Telecommunications	0.3068	*0.0101*	0.881193	0.1663*	0.8913
Oil and Gas	9.7778	0.2554	n/a	*-0.1358*	0.2554
Benchmark indices					
All-share	3.8550	0.2134	n/a	*-0.1549*	0.2134
Small Cap	0.5152	0.2563	n/a	*0.0080*	0.2563
Mid Cap	*0.0533*	*0.0098*	0.8935	0.1258*	0.9034

Source: Author's estimates
,,*** means that the coefficient is statistically significant at the 1%, 5% and 10% level*
Coefficients in italics are statistically insignificant
$\alpha_1 + \beta$- is a condition for stability for the univariate GARCH models

Table 4: **Post-crisis sample TGARCH (*p,r,q*)**

Sectors	**Ω**	**α_1**	**β**	**λ**	**$\alpha_1 + \beta$**
Basic materials	2.2104	0.0904	n/a	*-0.0240*	0.0904
Consumer goods	0.0368	*0.0089*	0.9242	0.0703*	*0.9331*
Consumer services	1.4438	0.1512	n/a	0.1295**	0.1512
Financials	0.8824	0.0907	n/a	0.1551*	0.0907
Health Care	0.0400	0.0493	0.8756	0.0849*	0.9249
Industrials	0.0256	*0.0100*	0.9069	0.1106*	0.9168
Technology	1.1797	0.0686	n/a	0.2164*	0.0686
Telecommunications	2.2324	0.2297	n/a	*0.0671*	0.2297
Oil and Gas	2.1208	0.4199	n/a	-0.1603*	0.4199
Benchmark indices					
All-share	0.8235	*0.0074*	n/a	0.2727*	*0.0074*
Small Cap	0.1983	0.2788	n/a	0.0987*	0.2788
Mid Cap	0.0096	0.0313	0.9165	0.0658*	0.9478

Source: Author's estimates
,,*** means that the coefficient is statistically significant at the 1%, 5% and 10% level*
Coefficients in italics are statistically insignificant
$\alpha_1 + \beta$- is a condition for stability for the univariate GARCH models

The inclusion of the lag of the volatility component in the individual sectors resulted in the continued presence of ARCH effects hence its removal. In the case of the Basic materials sector, a higher residual component of order 2, i.e. TGARCH (2, 1, 0), was estimated to capture all the volatility in the overall sample. In other sectors, namely, Consumer services, Healthcare, Telecommunications, Oil and Gas and Technology, a TGARCH (1, 1, 0) was able to capture all the volatility in the returns for the whole sample. As observed from Tables 1 to 4, the stationarity condition is satisfied for all the sectors and indices.

5.3.2a Whole sample period results

Table 1 results show that for Consumer goods, Industrials and Financials, the sum of α and β is close to 1, suggesting very high volatility persistence. The benchmark indices (i.e. All-share and Mid-cap) also show high levels of persistence. For the sectors that have a summation close to 1, a shock in the current period of the return generating process will take a long time to die out (Mandimika, 2010). The Consumer goods sector has the highest volatility persistence of 0.9583 relative to other sectors and benchmark indices. This was followed by the Financials sector (0.9336), All-share index (0.9332), Industrials sector (0.9233) and lastly the Mid-cap index (0.9288). Sectors with high persistence indicate that past information is more important than recent information.

A lower volatility persistence was experienced in Consumer services, Telecommunications, Small-cap and Health care respectively. These findings are similar to those of Arguile (2012) and the argument for such results is that these sectors are regarded as defensive in nature, hence they act contrary to the business cycle. A shock to any of the stocks in these sectors will not last long but dies out quickly.

All the coefficients in the TGARCH variance equation are significant at the 1% level. As indicated by equation *4* in chapter 4, the λ represents the asymmetric coefficient. The asymmetric coefficient is statistically significant for all models which implies that there is evidence of asymmetry in all the sectors and benchmark indices.

The TGARCH model results in Table 1 show that $\lambda > 0$, for all sectors (except the Oil and Gas) and benchmark indices. This means that bad news (or negative shocks) have a much greater impact on stock return volatility of each sector than good news (or positive shocks) of the same magnitude. The findings are congruent with other empirical studies (see Blasco *et al,* 2002; Arguile, 2012; Mandimika and Chinzara, 2012). Similar to the post-financial crisis period, the Oil and Gas sector shows that good news has a greater impact on stock return volatility than bad news.

5.3.2b Pre-financial crisis period

Table 2 shows there was asymmetry in all the chosen stock market sectors, since the asymmetry coefficient is statistically significant in all sectors. All the sectors have a positive sign for the asymmetric coefficient, which signals that bad news during this period had more impact than good news of the same magnitude. Volatility persistence is high in the following sectors: Consumer goods, Oil and Gas, Consumer services and Industrials. The benchmark indices which also recorded the highest volatility persistence are the All-share index and the Mid-cap index. The least volatility persistence during this period is found in the Basic materials, Health care, Telecommunication and Financials sectors. These findings are not entirely congruent with Arguile (2012) whose findings showed that all sectors and the All-share index had very high volatility persistence.

5.3.2c During financial crisis period

The results for this period are shown in Table 3. Only two sectors have a positive and significant asymmetric coefficient: these sectors are Consumer services and Telecommunications. High levels of persistence are also seen for these two sectors. For the benchmark indices, the Mid-cap index was the only index showing that bad news had more impact on stock return volatility than good news of a similar magnitude. Findings from this study show that in the Basic materials Financials, Health care, Industrials, Technology, Oil and Gas, All-share and Small-cap indices the asymmetric coefficient was insignificant. The plausible explanation for this could be that the overwhelming pessimism in the market amongst investors during the crisis period overshadows any individual effects of good and bad news thus making it challenging to detect the actual impact of the change in the stock return volatility. The mean of the residuals series for most of these sectors is negatively skewed thus supporting the claim of high level of pessimism during this period. Arguile (2012) also found similar results in the Financials, Health care and Technology sectors for the financial crisis period.

5.3.2d Post-financial crisis period

From Table 4 only the Basic materials sector and the Telecommunications sector show no evidence of asymmetry, as for both sectors the asymmetric coefficient is statistically insignificant. The rest of the sectors (except for the Oil and Gas) and benchmark indices show that asymmetry is present and bad news has a greater impact on stock return volatility than good news of the same magnitude. In the Oil and Gas sector the sign of the asymmetric coefficient is negative, which suggests that positive news has more impact on return volatility than bad news of the same magnitude. This is congruent with the positive skewness of the returns found in the post-crisis descriptive statistics. The Health care, Industrials and Mid-cap indices have the highest volatility persistence and the Technology, Basic materials, Financials, Consumer services, Telecommunications and Small-cap indices record relatively low persistence in volatility.

5.4 Differential impact of good news and bad news

Tables 5 and 6 summarize the absolute as well as differential impact of good news and bad news on the conditional variance for each sector and benchmark indices in the overall sample and sub-samples respectively. The results are a clear indication that in South Africa good news and bad news have a different impact on conditional volatility and the impact varies across different sectors. The magnitude of the impact of news on the conditional variance can be obtained from α and λ values. For example, looking at the whole sample, good news in the Basic materials sector increases volatility by 0.11units while the impact of bad news on the conditional variance is calculated by adding $\alpha_1 + \lambda$, thus an increase of 0.29 units (0.11 + 0.18). This shows that bad news has a greater impact on volatility than good news of the same magnitude in this sector.

In Table 5, good news is more pronounced in the Technology, Health care, Small-cap, Telecommunications, Oil and Gas relative to all other sectors and indices. This means that when good news enters the market these sectors experience a large increase in volatility relative to other sectors. However, for some of the same sectors, namely, Technology, Telecommunications and Small-cap, the stock return volatility as a result of bad news is even larger than that of good news cementing the fact that investors in these sectors are also more sensitive to bad news.

Table 5: **Whole sample period differential impact**

	TGARCH		
Sectors	**Good news (α_1)**	**Bad news ($\alpha_1 + \lambda$)**	**Difference (%)**
Basic materials	0.1071	0.2849	166.02
Consumer goods	0.0448	0.1132	152.63
Consumer services	0.1965	0.3741	90.42
Financials	0.0574	0.1613	181.0
Health Care	0.2585	0.3169	22.59
Industrials	0.0488	0.1506	208.62
Technology	0.3899	0.5716	46.62
Telecommunications	0.2230	0.3853	72.79
Oil and Gas	0.3676	0.2956	-19.58
Benchmark Indices			
All-share	0.0391	0.1422	263.44
Small Cap	0.2425	0.3470	43.09
Mid Cap	0.0485	0.1288	165.38

Source: Author's estimates

Table 6: **Differential impact for Pre-crisis, During crisis and Post-crisis period**

	Pre-crisis			**During-crisis**			**Post-crisis**		
Sectors	**Good news (α_1)**	**Bad news ($\alpha_1 + \lambda$)**	**Difference (%)**	**Good news (α_1)**	**Bad news ($\alpha_1 + \lambda$)**	**Difference (%)**	**Good news (α_1)**	**Bad news ($\alpha_1 + \lambda$)**	**Difference (%)**
Basic materials	0.1735	0.3677	111.97	0.1527	*0.1585*	3.80	0.0904	*0.0664*	n/a
Consumer goods	0.0611	0.1297	112.24	n/a	n/a	n/a	0.0089+	0.0703	689.89
Consumer services	0.0640	0.1534	139.81	0.0071	0.1299	1725.92	0.1512	0.2807	85.64
Financials	0.2639	0.5110	93.62	0.0943	*0.1725*	n/a	0.0907	0.2458	171.06
Health Care	0.2364	0.3516	48.69	0.0962	*0.1894*	n/a	0.0493	0.1342	172.10
Industrials	0.0585	0.1622	177.27	0.1102	*0.1023*	n/a	0.0100+	0.1106	1006.00
Technology	0.3317	0.5288	59.39	0.1056	*0.1305*	n/a	0.0686	0.2850	315.25
Telecommunications	0.2473	0.3916	58.34	0.0101+	0.1663	1546.53	0.2297	*0.2968*	n/a
Oil and Gas	0.0551	0.0991	80.05	0.2554	*0.1195*	n/a	0.4199	0.2597	-38.16
Benchmark Indices									
All-share	0.0553	0.1620	192.87	0.2134	*0.0585*	n/a	0.0074+	0.2727	3585.14
Small Cap	0.0440	0.2313	425.63	0.2563	*0.2643*	n/a	0.2788	0.3775	35.40
Mid Cap	0.0508	0.1801	254.56	0.0098+	0.1258	1183.67	0.0313	0.0971	210.40

Source: Author's estimates
Note- The values in italics show that the asymmetric coefficient is insignificant
+, show that asymmetry is present but the lag of the residuals is insignificant

Shi *et al.* (2015) also found that bad news had more impact in the IT sector compared to other sectors. The findings from Table 5 show that in all sectors except the Oil and Gas sector, bad news has a greater impact on volatility than good news. Despite not finding asymmetry in most of the sectors during the global financial crisis period, it is evident that the difference in magnitude between good and bad news on return volatility in the post-crisis increased in most sectors relative to the pre-crisis period. This suggests that investors became more sensitive to bad news after the crisis, possibly because of heightened nervousness engendered by the crisis itself.

The results from the overall sample also show that in the Consumer goods sector, Industrials sector and All-share index, the differential effects between bad news and good news are quite big compared to other sectors. This amplified effect of bad news on the return volatility can mainly be attributed to the high volatility in the post-crisis period. Furthermore, Table 5 illustrates that the impact on the return volatility of the All-share index and Mid-cap index as a result of bad news is less than that of all sectors except for the Consumer goods sector. This implies that individual sectors are more responsive to negative news than the average market. The results also show support of the performance of sectors on the JSE after the global financial crisis. Sectors such as the Basic materials and Industrial which recorded low market capitalisation growth rate after the financial crisis showed high amplified effects of bad news on stock return volatility. The Health Care and Technology sectors which recorded the highest market capitalisation growth rate on the JSE had a low amplified effect of bad news on stock return volatility. This implies that the impact of good and bad news on stock return volatility can also highlight the sectoral performance.

For the Oil and Gas sector, an interesting and unusual result is seen in both Tables 5 and 6. The findings show that the return volatility in the Oil and Gas sector reacts more to good news than bad news of the same magnitude for the overall sample. However, looking at the breakdown from Table 6, this sector did not react in the same was in either pre-crisis or during the global financial crisis, but only in the post-crisis period. This unusual finding is therefore not something that is innate to the Oil and Gas sector, but it was only peculiar to the post-crisis period. It is unclear why the sudden shift occurred. A possible explanation is that for a large part of this post-crisis period (until 2014), the price of oil remained very high, making this sector very profitable relative to other sectors that were still battling from the impact of the crisis on their earnings. Investors therefore did not react strongly to negative news for companies within this sector, but they reacted more to good news, possibly because all the other sectors were still struggling. When the price of oil fell post-2014 the fall was initially expected to be short-lived. Moreover, the rand had also weakened significantly, thus providing an earnings hedge for this sector whose prices are set in US dollars. Because companies in this sector were selling petrol at the rand-equivalent global price, investors remained optimistic about the sector's future, thus not being so concerned with bad news and reacting more to good news. Krishnamurti, *et al.* (2013) argue that the positive asymmetry effect suggest that investors chase stocks with rising prices rather than push down prices by selling shares when bad news hit the market. Such a return chasing behaviour amongst investors is peculiar in a bull market such as the post-crisis period in this study. Coffie (2015) found positive asymmetry in Nigerian stocks and argued that the positive asymmetry resulted from Nigerian investors being more responsive to momentum stocks (i.e. price rising stocks).

5.4.1 Discussion of volatility asymmetries within and across sectors

5.4.1a Volatility asymmetry within sectors

Volatility asymmetry within sectors (except for the Oil and Gas sector) in this study is mainly driven by negative news. In order to address one of the objectives of this study, possible explanations have been provided to help understand why bad news rather than good news has a greater impact on stock return volatility in these sectors.

Volatility asymmetry within sectors can be explained by financial leverage effect hypothesis (see Wu, 2001 and Hibbert *et al.*, 2008). When bad news filters into the market, firms within sectors become more leveraged relative to falling earnings causing volatility in stock returns to increase whereas good news will cause the firms to be less leveraged when earnings rise reducing the stock return volatility. In this case, investors are more likely to be sensitive to negative news rather than positive news because of the future uncertainty resulting from increased risk of company failure.

Extrapolation bias is also one of the possible explanations of why bad news on stock return volatility has greater impact than good news. Extrapolation bias as defined by (Hibbert *et al.*, 2008) is the extrapolation of past events to form a forecast, in combination with those who believe in recent events are representative of the future. The daily stock market declines are argued to occur more than market rallies (see, Bakshi and Madan, 2006) thus this influence fear amongst investors that negative returns will cause the market to decline further. As a consequence investors appear to possess a legitimate reason to fear a potential severe market decline hence causing them to react more to bad news more than positive news.

Another psychological phenomenon known as overconfidence coupled together with observed gender differences in risk-taking can possibly explain this volatility asymmetry within sectors. According to Varian (2010), psychologists commonly find men to display overconfidence in their own abilities while women tend to be more cautious. This implies that men tend to trade excessively, which might have financial repercussions. Because investment traders in South Africa are mainly men (Masote, 2013), more risky investments are likely to occur through overconfidence investment decisions, leading to greater losses if bad news enters the market. This then means investors will have to pay more attention to bad news than to good news.

Another possible explanation why volatility asymmetry within sectors is mostly driven by bad news is the nature of investors within these sectors. For example, investors focusing on the Technology sector, might be more loss averse rather than the risk averse investors generally found in the Financial sector (see Hammoudeh *et al.*, 2009). Loss averse investors tend to place excessive weight on negative information even though the magnitude of the impact is the same as that of positive information (Varian, 2010). For this reason, loss-averse owners of stocks are very reluctant to incur short-term losses even when it would be advantageous over the longer-term to do so. Such behaviour would cause investors to react more to bad news than good news, thus resulting in volatility asymmetry within such sectors to being driven by bad news.

The role of the media is another possible explanation for the amplified effect of bad news on volatility asymmetry within sectors. Soroka (2006) found that journalists prioritise publishing negative information more than positive information because of the belief that publishing negative news plays a role in holding the government and companies accountable. However, the constant publication of negative news by the media can also have a significant impact on individual perceptions. The constant dissemination of negative news by media publications influences investors' perceptions, thereby causing them to react more to bad news than good news in all the sectors except for the Oil and Gas sector.

5.4.1b Volatility asymmetry across sectors

Table 6 shows that the impact of bad news on stock return volatility across sectors also varies. There are also some possible explanations that can be explored to understand this kind of behaviour across sectors. Investor expectation about the future of the companies that make up sectoral indices is one of the reasons why volatility asymmetry varies across sectors. According to Mubarik and Javid (2009), investor perceptions can influence the interpretation, processing and analysis of new information. This means that as bad news enters the market investors' reaction to the news differs across sectors resulting in volatility asymmetry to vary across sectors. For example, news about an increase in unemployment may be regarded by investors as good news for some sectors but bad news for other sectors, which means that return volatility response will vary. Investors might view an increase in unemployment as bad for the Consumer goods sector because it means that firms in this sector will lose out on sales, but good for the Basic materials sector because the increased availability of cheap labour will help them reduce operating costs and increase profits.

Information flow might also be used to explain the varying of volatility asymmetry across sectors. An example is the negative news pertaining to the potential downgrade of South Africa's sovereign credit ratings. This negative news is likely to impact more on the Financials sector and the Consumer goods sector than other sectors in this study. Bukula (2016) argues that consumer confidence will decline as a result of a downgrade because of uncertainty about their financial future, resulting in their cutting expenditure on consumer goods. Firms in the Consumer goods sector will therefore be heavily impacted by such bad news as they will lose out on sales. Bukula (2016) also argues that if the country's credit ratings are cut to sub-investment grade, there will be shortage of funds and increased cost of credit. Banks, which dominate the Financials sector index, will be heavily impacted by such bad news as they will be unable to meet their customers' demand of credit. Such bad news is therefore likely to be more detrimental in these two sectors than in other sectors (for example Basic materials whose markets are mainly global), leading to stock return volatility in reaction to bad news being greater in Financials and Consumer goods than for most of the other sectors.

The media plays an additional pivotal role in helping understand volatility asymmetry across sectors. Saxton and Anter (2013) found that the ability of the new media to enhance individuals' capacity to produce and disseminate knowledge results in a decrease in information asymmetry and insider trading in the stock market. However, the uneven distribution of information by the media can cause volatility asymmetry to vary across sectors. Shi *et al.* (2015) found that the marginal effect of each news release on return volatility is higher in companies that have lower news flow. This implies that there are companies that belong to sectors that get more media attention than others. For example, companies in the Financial sector may receive more media attention than companies in other sectors, which implies that information asymmetry between corporate insiders and the average investor is reduced. The implication of this is that investors in this sector will have adequate knowledge of events occurring to companies in this sector thereby allowing them to make informed investment decisions relative to investors in other sectors with companies that receive less media attention (Shi *et al.*, 2015). The impact of bad news on stock return volatility in the Financial sector will be expected to be less than that of other sectors. The reasoning being that for the other sectors, as bad news enters the market and without adequate information, investors are likely to overreact to such news.

The amplified effects of bad news on stock return volatility in the Industrials and Financials sectors relative to other sectors can also be explained by the role of investor sentiment. Uygur and Tas (2014) assert that sentiment drives the investment decision of investors who are not fully rational (i.e. noise traders). Because of the strong trade-off between mean and variance any reaction to changes in sentiment can be risky and costly. Agyros (2012) found a significant relationship between investor sentiment and South African share returns. The increased participation of noise traders in these two sectors may be motivated by the fact that they might have the highest free-float market capital relative to other sectors, creating additional liquidity for both individual and institutional investors in the market (Uygur and Tas, 2014). With the increased participation of noise traders, sentiment driven and more risky investment becomes increasingly important. Baker and Wurgler (2006) found that when sentiment driven investment is important due to increased levels of participation of noise traders in the market, prices will deviate from the level that would reflect a positive mean-variance trade-off. This means that the impact of bad news on stock return volatility in such sectors is likely to be greater than the impact of bad news in other sectors.

Trading volume also helps in understanding volatility asymmetry across sectors. Mubarik and Javad (2009) note that there is a significant interaction between trading volume and stock return volatility. In the South African stock market, Basic materials, Consumer goods and Consumer services sectors have the highest market capitalisation and turnover (Mayer, 2013). This implies that these sectors comprise stocks that are more heavily traded on a daily basis, and if bad news enters the market its impact is more likely to be greater in these sectors compared to other sectors thus causing the variation in volatility asymmetry.

Lastly, the nature and characteristics of different sectors might also explain why the impact of bad news on stock return volatility is amplified in some sectors and not in others. The magnitude of the difference between good news and bad news on stock return volatility in the Health care sector is the lowest relative to other sectors and benchmark indices. Basic medication and health services are a necessity hence there is consistent demand by consumers even in the presence of bad news in the market (Petroff, 2013). Investors in companies which makes up this sector are optimistic about their future cash flow since there is guaranteed demand so they will not react much to the negative news causing the return volatility to be less than that of other sectors. In the wake of negative news, the demand by consumers will possibly decrease but because people still need the basic necessities the fall in demand will not be much relative to other sectors for example Financials or Basic materials that are cyclical in nature (Petroff, 2013).

5.5 Summary

This chapter focused on reporting and analysing the findings pertaining to issues surrounding the impact of good and bad news on stock return volatility across various sectors in South Africa. Firstly, stationarity tests done using the ADF and KPSS tests showed that for both the sub-samples and the overall sample, all sectors' return series were stationary in level terms. Using the estimated regression in chapter 4, the mean equation was estimated following an ARMA (p, q) model and findings shown in Appendix A (Table A4.1 to A4.4) revealed that there were ARCH effects in all sectors (except the Consumer goods during the crisis period) and indices thus enabling the employment of the univariate GARCH models.

The TGARCH and EGARCH models were used to analyse the impact of the good and bad news on stock return volatility. Only the TGARCH results for sub-samples and the overall sample were reported because the EGARCH model violated the stability condition in most samples. In the TGARCH results, leverage effects are present in all sectors except for during the crisis period. Volatility persistence is also found to be present in most of the sectors in all samples. Asymmetry in stock return volatility is as a result of the bad news in all sectors except for the Oil and Gas sector during the post-crisis period and in the overall sample. Such findings are consistent with other empirical studies (see Chinzara and Aziakpono, 2009; Mandimika and Chinzara, 2012; Shi *et al.*, 2015). The unusual result for the Oil and Gas sector was possibly because in the post-crisis period (until 2014) whilst other sectors were still battling from the after effects of the financial crisis, this sector remained very profitable so investors remained optimistic even when negative news filtered into the market.

The highest volatility persistence was found in Consumer goods, Financials, Industrials, All-share and Mid-cap indices for the whole sample period. This means that in these sectors shocks will die away slowly and it will take a long period for mean reversion to occur. Table 5 showed that the impact of bad news on stock return volatility was more pervasive in the Technology sector, Telecommunications sector, Consumer services sector and Small-cap index. The Oil and Gas sector showed that positive news has more impact than bad news of the same magnitude. The magnitude between good and bad news for some sectors in the overall sample can be attributed partially to global financial crisis and the post-crisis period. Despite the fact that during the crisis many sectors showed no evidence of asymmetry (except for Consumer services, Telecommunications and Mid-cap), the amplified effects of bad news on stock return volatility in the post-crisis period could also be attributed to the crisis simply because when comparing the post-crisis and pre-crisis period, the impact of bad news on volatility had increased significantly for each sector after the financial crisis except the Consumer services, Small-cap and Mid-cap.

To address the main objective of this study, the volatility asymmetry within and across sectors was discussed in this chapter as well and possible explanations as to why bad news has more impact on stock return volatility than good news were provided. Within sectors, issues such as overconfidence, extrapolation bias, the role of the media in publishing more negative news than positive news and its impact on investor perception, and the nature of investors were identified as possible explanations. Volatility asymmetry across sectors can be explained possibly by the information flow in sectors, the uneven distribution of information by the media, the nature and characteristic of the sectors, investor expectations, investor sentiments and trading volumes. The next chapter covers the summary and conclusion of this study.

CHAPTER 6. CONCLUSION

6.1 Summary of the study and conclusion

The study analysed the impact of good news and bad news on stock return volatility of nine sectors and three benchmark indices of the South African equity market. The aim was to identify sectors in which good or bad news dominates and provide justification as to why a certain type of news takes precedence over the other. The study also examined whether the impact of good news and bad news was symmetrical or asymmetrical. To achieve these objectives daily data and univariate asymmetric GARCH models were employed. The TGARCH and EGARCH were found to be the most appropriate models to help in achieving both objectives of the study.

To carry out the analysis, the first step involved looking at the theoretical foundations underlying the stock market. The relevant theoretical literature includes the Asset Pricing Theory (APT) models, the Efficient Market Hypothesis (EMH) and Behavioural Finance (BF). These theories are relevant to the financial market because they aid in explaining how investors formulate their investment decisions and also how they behave with regards to information they receive on a daily basis. The next step was a review of the related empirical literature that focused on modelling stock return volatility of markets as a whole and also across various sectors. The empirical literature was reviewed for developed and developing markets, including South Africa. The common finding from the literature was that the impact of good news and bad news is asymmetrical, with bad news having more impact on stock return volatility than good news of the same magnitude. It was also found that volatility in stock markets is very persistent in many sectors and benchmark indices. In addition, the empirical studies also revealed that various sectors react differently to both good and bad news.

To achieve the objectives of this study, the data was analysed as a whole sample from January 1997 to August 2016 and also as sub-samples (pre, during and post- the global financial crisis of 11 October 2007- 3 March 2009). The reason for employing sub-samples was to observe if the findings from the overall sample can also be attributed to any of the sub-samples. Daily closing prices were converted into return series. Stationarity tests were then carried out using the ADF and KPSS stationarity tests for each sample. For all variables to be modelled, the differences in the logarithmic values of the phenomena being modelled were tested to ensure stationarity. This is an important precursor to effective model estimation. The results reported showed that all the sectors and benchmark indices were stationary in level terms in both tests conducted. Autocorrelation tests and ARCH effects tests were conducted on the estimated mean equation for each sector and index. For all sectors and indices in the overall sample and sub-samples - except Consumer goods during the financial crisis - the results found no autocorrelation and ARCH effects were present.

Univariate GARCH models, namely the TGARCH and EGARCH were employed. These two models are pertinent to this study because they distinguish the asymmetrical impact of good news and bad news on stock return volatility across various sectors. The EGARCH model was later dropped from the analysis because the stability condition for most of the sectors in all samples was violated. Only findings obtained from the TGARCH model were therefore analysed in detail. Higher component order TGARCH models were employed for some sectors rather than the most parsimonious standard TGARCH (1, 1, 1) model because of the continued presence of ARCH effects.

The TGARCH results showed that there was asymmetry across all sectors and benchmark indices in the whole sample, pre-crisis and post-crisis samples. Bad news was found to affect stock return volatility more than good news of the same magnitude in all sectors except the Oil and Gas sector. The Oil and Gas sector showed that positive news has more impact on stock return volatility than negative news of the same magnitude in the post-crisis sample and the whole sample. During the financial crisis period, the results for most sectors (except Telecommunications, Consumer services and Mid-cap) showed that there was no asymmetry. A possible explanation is that during this period there was so much pessimism amongst investors that the individual impact of good or bad news could not be identified. The mean for the residuals for all sectors were all negative, thus supporting the claim of a high level of pessimism during this period. A possible explanation for the findings in the Oil and Gas sector is that investors are more responsive to momentum stocks (i.e. price rising stocks). Immediately after the global financial crisis, the Oil and Gas sector was possibly the only sector in which companies were still realising significant profits and as such investors responded more to positive news than negative news entering the market.

It was also found that in the whole sample, volatility was highly persistent in the following sectors and indices - Consumer goods, All-share, Mid-cap, Industrials and Financials. This suggests that in these sectors a shock will take a longer period to die out. The least volatility persistent sectors were Consumer services, Telecommunication, Small-cap, Healthcare, Basic material and Technology. This implies that amongst these sectors mean reversion occurs within a very short period.

The differential impact of good and bad news (Table 5) showed that good news impacted more strongly in the Technology, Oil and Gas and Health care sectors than other sectors. However, for the Technology sector the impact of bad news on return volatility was significant larger than that of good news. This suggests that investors in this sector are more responsive to negative news. Other sectors in which the impact of bad news was amplified are Telecommunications, Consumers services and Basic materials and Small-cap. Except for the Consumer goods, all the sectors experienced higher volatility from bad news than the benchmark indices. Individual sectors react more to bad news than the overall market.

The impact of bad news on stock return volatility for some sectors can be attributed to the global financial crisis. When a comparison is made between the pre-crisis and post-crisis periods (Table 6), it is clear that in most sectors bad news has a more amplified effect on return volatility after the crisis. For example, the differential percentage impact between good and bad news for Consumer goods increased from 112.24% to 786%. For the Industrials sector it increased from 177.27% to 1108.23%, for Technology from 59.39% to 315.25% and for the All-share index from 192.87% to 3686.08%.

A main objective of this study was to explain why the return volatility in most sectors is negatively correlated. Volatility asymmetry within sectors was explained by factors such as the preponderance of negative information over positive information in the media. It was argued that the media tends to publish more bad news than good news, in order to ensure that both the government and companies are being held accountable for their actions (Soroka, 2006). This flooding of bad news in the market can influence investor perceptions, thus causing them to be more responsive to negative news than good news.

Possible explanations for volatility asymmetry within sectors were financial leverage, the nature of investors in each sector (for example loss-averse investors place more emphasis on negative information than positive information of the same magnitude), extrapolation bias and overconfidence. Varian (2010) argues that male investors tend to be more overconfident than their female counterparts, causing them to engage in risky investments in more volatile sectors that are more likely to result in large losses when bad news enters the market.

Variation across sectors of volatility asymmetry in response to bad news was explained by the uneven distribution of information amongst sectors in the media. Other possible explanations include investor expectations about the future of companies within sectors, trading volumes, investor sentiment, the nature and characteristics of individual sectors and information flows in each sector. With regards to investor sentiment, the Industrial and Financial sectors were found to be attractive mostly to noise traders that employ sentiment in their investment decisions. The increased participation of such traders in the market is likely to cause the impact of bad news in these sectors to be much greater relative to other sectors.

Overall, the results indicate that the stock return volatility of individual sectors of the South African equity market is driven mainly by bad news (except for Oil and Gas) and that leverage effects exist in all the sectors and in the benchmark indices. The global financial crisis increased the differential impact of good and bad news in the post-crisis period. The impact of the global crisis thus has an important influence on the findings for the overall sample.

6.2 Investor and Policy Implications

The findings from this study have implications for investors' decision-making strategies. Investors need to have a clear understanding of the impact of good news and bad news on return volatility. Knowledge of the sectors that are more affected by bad news than good news, enables them to manage their portfolios more effectively. They can also formulate hedging strategies that can reduce losses caused by increases in volatility, by identifying sectors that are least affected when certain information enters the market. The understanding of volatility asymmetry on stocks in different economic sectors is pivotal in helping investors manage risk through effective portfolio diversification. Investors can also gain knowledge of some of the non-fundamental factors that influence stock return volatility. These factors arise from investors' individual behaviour such as representativeness, extrapolation bias, sentiment driven investment decisions and also the role of expectations and interpretation of information.

For policy makers, this study provides an understanding of the implications of policies they implement on stock prices in different sectors. By understanding these policy implications, policymakers will become aware of the sectors that will be most affected by stock return volatility and how detrimental this effect is on a country's growth. According to Mandimika and Chinzara (2012), increasing volatility can be detrimental to the economy as it leads to capital outflows which could amplify financial instability. The findings might assist policy makers avoid decisions that can jeopardise the macroeconomic stability of the country triggered via the stock market.

6.3 Areas of Further Research

This study has its own shortfalls. It focused only on good news and bad news measured by the sign of the error term to determine the impact on stock return volatility across South African sectors. Further research can be done on stock return volatility using specific news events as indicators of good and bad news. Actual news versus anticipated news can be employed and used as a measure of the surprise component of good and bad news on stock return volatility.

This study employed univariate GARCH models to capture stock return volatility and asymmetry in the sectors of the South African equity market. An extension of the models to a multivariate GARCH framework can be incorporated into future research to analyse the relationship between sectoral volatility. Investors will then be able to identify if there are volatility spill-over effects across sectors in the South African equity market, allowing them to gain full knowledge of sectoral linkages and to devise strategies around such information.

While this study was only done at a super-sectoral level it would be worthwhile extending it to sub-sectors to get a clearer picture of the industries that drive stock return volatility in these super-sectors. A study of the sub-sectors can also help investors obtain additional information on areas where they can implement hedging strategies thus allowing them to manage risk effectively. Further research can also focus on the 'primitive factors' of stocks that are influenced by news received by the market which then affects stock prices. The 'primitive factors' of stocks include the risk-free rate of interest, the expected dividend/earnings growth rate and the risk premium. Knowledge of the impact of good and bad news on these 'primitive factors' is relevant for investors when managing portfolios and formulating hedging strategies.

Researching the relationship between the characteristics of stocks listed on the market and the stock return volatility of each sector would also be worthwhile. Different sectors comprise of firms with different market capitalisations, which means that certain sectors are larger than others. The impact of market size might play a role in explaining return volatility in sectors. Lastly, an extension of the research could be to employ a regime switching GARCH models to account for the possible non-linearities.

REFERENCES

ABDALLA, S.Z.S and WINKER, P., 2012. Modelling stock market volatility using univariate GARCH models: Evidence from Sudan and Egypt. *International Journal of Economics and Finance,* 4(8): 161- 176.

ACKERT, L.F and DEAVES, R., 2010. *Behavioural finance: Psychology, Decision-making and Markets*. South-Western Cengage Learning: Ohio, USA.

AGGARWAL, R, INCLAN, C and LEAL, R., 1999. Volatility in emerging stock markets. *The Journal of Financial and Quantitative Analysis,* 34: 33-55.

ARGUILE, W.P., 2012. *Performance of defensive shares on the JSE during financial crisis: Evidence from analysis of returns and volatility*. Unpublished Masters Thesis. Grahamstown: Dept of Economics, Rhodes University.

ARGYROS, R., 2012. *The power of investor sentiment: An analysis of the impact of investor confidence on South African financial markets*. Unpublished Masters Thesis. Grahamstown: Dept of Economics, Rhodes University.

ALBERG, D, SHALIT, H and YOSEF, R., 2008. Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics,* 18(15): 1201-1208.

AL-JAFARI, M.K., 2012. An empirical investigation of the day of the week effect on stock returns and volatility: Evidence from Muscat securities market. *International Journal of Economics and Finance,* 4(7):141-149.

AL-NAJJAR, D., 2016. Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market. *Asian Journal of Finance and Accounting,* 8(1):152-167.

BAILEY, R.E., 2005. *The economics of financial markets*. Cambridge University Press: New York.

BAKER, M. and WURGLER, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance* 61(4): 1645 - 1680.

BAKER, H.K and NOFSINGER, J.R., 2010. *Behavioural Finance: Investors, Corporations and Markets*. John Wiley and Sons: New Jersey.

BAKRY, W. K., 2006. *A panel in GARCH analysis in stock return volatility in an emerging market: A case study of Egypt.* Unpublished Masters Thesis. Sydney: School of Economics and Finance: University of Western Sydney.

BAKSHI, G and MADAN, D., 2006. Crash discovery in the stock market. Working Paper, University of Maryland.

BALL, R., 2009. The global financial crisis and the efficient markets hypothesis: What have we learned? *Journal of Applied Corporate Finance,* 21(4): 8 – 17.

BANUMATHY, K and AZHAGAIAH, R., 2015. Modelling stock market volatility: Evidence from India. *Managing Global Transition,* 13(1): 27-42.

BARBERIS, N and SHLEIFER, A., 2003. Style investing. *Journal of Financial Economics,* 68(2): 161 - 199.

BARBERIS, N and THALER, R., 2003. A survey of behavioural finance. In G.M. Constantinidis, Harris, Mand Stulz, R.M (eds), *Handbook of the Economics of Finance.* New York: Elsevier.

BARUNIK, J., KOCENDA, E and VACHA, L., 2015. Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. *Journal of Financial Markets,* 27: 55-78.

BAXTER, R., 2009. *The Global Economic Crisis and its Impact on South Africa and the country's mining industry*. [Online]. Available: https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/51/Roger+Baxter.pdf. [Accessed 11 October 2016].

BIRZ, G and LOTT, J.R., 2011. The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking and Finance,* 35: 2791-2800.

BLASCO, N., CORREDOR, P and SANTAMARIA, R., 2002. Is bad news cause of asymmetric volatility response? A note. *Applied Economics*, 34: 1227-1231.

BLASCO, N., CORREDOR, P., DEL RIO, C and SANTAMARIA, R., 2005. Bad news and Dow Jones make the Spanish market go round. *European Journal of Operation Research*. 163: 253-275.

BLOOMBERG, 2015. *South African markets rattled as Zuma fires finance minister*. [Online]. Available: http://www.bloomberg.com/news/articles/2015-12-10/rand-plunges-in-longest-losing-streak-in-two-years-as-nene-fired. [Accessed 14 October 2016].

BOLLERSLEV, T, 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalised ARCH model. *Review of Economics and Statistics,* 72: 498-505.

BOURI, E and SALLOUM, C., 2015. Is bad news good news in the Lebanese stock market? An asymmetric model of return volatility. [Online] Available: https://www.researchgate.net/publication/273001420

BOYD, J.H., HU, J and JAGANNATHAN, R., 2005. The stock market reaction to unemployment news: Why bad news is usually good news for stocks. *The Journal of Finance,* 60(2): 649-672.

BROOKS, C, 2008. *Introductory Econometrics for Finance*. (*2e*). Cambridge University Press: New York, USA.

BULUKA, M.S., 2016. Downgrade and recession: a catastrophe for SMEs. *BankerSA*. 25 November. pp 18 and 19.

CHEN, N., ROLL, R. and ROSS, S., 1986. Economic forces and the stock markets. *Journal of Business*, 59: 383 - 403.

CHEN, C.W.S., CHIANG, T.C and SO, M.K.P., 2003. Asymmetrical reaction to US stock-return news: evidence from the major stock markets and based on a double-threshold model. *Journal of Economics and Business,* 55:487-502.

CHINZARA, Z. and AZIAKPONO, M.J., 2009. Dynamic returns linkages and volatility transmission between South African and world major stock markets. *Studies in Economics and Econometrics*, 33 (3), 69-94.

CHINZARA, Z., 2011. Macroeconomic uncertainty and conditional stock market volatility in South Africa. *South African Journal of Economics*, 79(1): 27-49.

COFFIE, W., 2015. Modelling and Forecasting the Conditional Heteroscedasticity of stock returns Using Asymmetric Models: Empirical Evidence from Ghana and Nigeria. *Journal of Accounting and Finance,* 15(5): 109-123.

DANIEL, K, HIRSHLEIFER, D and SUBRAHMANYAM, A., 1998. Investor psychology and security market under- and overreaction. *Journal of Finance,* 52(3): 1-33.

DEKPEN, C.A., 2001. Good News, Bad News and GARCH Effects in stock return data. *Journal of Applied Economics*, 4(2): 313-327.

DIAZ, A and JARENO, F., 2009. Explanatory factors of inflation news impact on stock returns by sector: The Spanish case. *Research in International Business and Finance,* 23:349-368.

DULWICH, E., 2006. *The impact news has upon stock price volatility: An investigation into the impact major BBC news reports have upon the FTSE 100*. Unpublished Masters Thesis. Aarhus School of Business: Dept of ASB. Erhvervsøkonomisk Institut.

ENDERS, W., 2010. *Applied Econometric Time Series.* (*3e*). John Wiley & Sons: River Street, New Jersey.

ENGLE, R. F., 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50, 987-1007.

ENGLE, R and Ng, V., 1993. Measuring and testing the impact of news on volatility. *Journal of Finance,* 48: 1749-1778.

FAMA, E. F., 1965. The behaviour of stock market prices. *Journal of Business,* 38(1): 34-105.

FAMA, E. F., 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance,* 25(5): 383 – 417.

FAMA, E. F., 1998. Market efficiency, long-term returns and behavioural finance. *Journal of Financial Economics,* 49: 283-306.

FAMA, E. F and FRENCH, K., 2004. The capital asset pricing model: Theory and Evidence. *Journal of Economic Perspective,* 18(3): 25-46.

FORBES, W., 2009. *Behavioural Finance*. Chichester, United Kingdom: John Wiley & Sons.

FRIMPONG, J. M and OTENG-ABAYIE, E. F., 2006. Modelling and Forecasting volatility of Returns on the Ghana Stock Exchange Using GARCH Models. *American Journal of Applied Sciences,* 3(10): 2042-2048.

FROOT, K. A, SCHARSTEIN, D and STEIN, J. C., 1992. Herd on the street. Informational efficiency in a market short-term speculation. *Journal of Finance,* 47: 1451 – 1484.

FUNKE, N and MATSUDA, A., 2006. Macroeconomic News and Stock Returns in the United States and Germany. *German Economic Review*, 7(2): 189-210.

GLOSTEN, L. R, JAGANNATHAN, R and RUNKLE, D. E., 1993. On the Relation between Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48, 1779-1801.

GOODSPEED, I., 2013. The Equity Market. *South African Institute of Financial Markets.* 1-192.

HAMMOUDEH, S. M., YUAN, Y and McALEER, M., 2009. Shock and Volatility spill-over among equity sector of the Gulf Arab Stock markets. The Quarterly Review of Economics and Finance, 49: 829-842.

HARTMAN, M. A and KHAMBATA, D., 1993. Emerging stock Markets. *Columbia Journal of World Business,* 28(2): 82-366.

HENRY, O., 1998. Modelling the asymmetry of stock market volatility. *Applied Finance Economics,* 8(2): 145-153.

HIBBERT, A.M., DAIGLER, R.T and DUPOYET, B., 2008. A behavioural explanation for the negative asymmetric return volatility relation. *Journal of Banking and Finance,* 32; 2254-2266.

HOU, A. J., 2013. Asymmetry effects of shocks in Chinese stock market volatility: A generalised additive nonparametric approach. *Journal of International Financial Markets, Institutions and Money,* 23: 12-32.

HOU, Z., KEANE, J., KENNAN, J and WILLEM Te VELDE, D., 2015. *The oil price shock of 2014: drivers, impact and policy implications*. [Online]. Available: https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/9589.pdf. [Accessed 16 October 2016].

HOWELLS, P and BAINS, K., 2008. *The Economics of Money, Banking and Finance* (*4e*). Pearson Education Limited: Harlow, England.

HUBERMAN, G and WANG, Z., 2005. Arbitrage pricing theory. *Federal Reserve Bank of New York Staff Reports,* 216: 1-18.

JOHANNESBURG STOCK EXCHANGE, 2017. *JSE Overview*. [Online]. Available: https://www.jse.co.za/about/history-company-overview. [Accessed 21 March 2017].

KEYNES, J. M., 1936. *The state of long-term expectation. The General Theory of Employment, Interest and Money Vol. 7*. London: Macmillan: 147−164.

KGOSIETSILE, O., 2014. *Modelling and Forecasting the volatility of JSE returns: A comparison of competing univariate GARCH models*. Unpublished Masters Thesis. Johannesburg: Wits Business School: University of the Witwatersrand.

KOVAČIĆ, Z. J., 2008. Forecasting volatility on the Macedonian Stock Exchange. *International Research Journal of Finance and Economics,* 18: 182-212.

KRISHNAMURTI, C., TIAN, G.G., XU, M and LI, G, 2013. No news is not good news: evidence of intra-day return volatility-volume relationship in Shanghai Stock Exchange. *Journal of the Asian Pacific Economy,* 18(1): 149-167.

KWIATKOWSKI, D., PHILLIPS, P.C.B., SCHMIDT, P and SHIN, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics,* 54: 159-178.

LAAKKONEN, H and LANNE, M., 2008. Asymmetric news effects on volatility: Good vs. Bad news in good vs. bad times. *Munich Personal RePEc Archive (MPRA),* 207: 1-21.

LAMOUREUX, C and LASTRAPES, W. D., 1990. Heteroskedasticity in stock return data: Volume versus GARCH effects. *Journal of Finance,* 45: 221-229.

LIAU, Y and YANG, J. W., 2008. The mean/volatility asymmetry in Asian stock markets. *Applied Financial Economics,* 18: 411-419.

LINTNER, J., 1965. Security prices, Risk and Maximal Gains from Diversification. *Journal of Finance,* 20(4): 584 - 615.

MABHUNU, M, 2004. *The market efficiency hypothesis and the behaviour of stock returns on the JSE securities exchange.* Unpublished Masters Thesis. Grahamstown: Dept of Economics, Rhodes University.

MAKHWITING, M. R., LESAOANA, M and SIGAUKE, C., 2012. Modelling volatility and financial market risk of shares on the Johannesburg stock exchange. *African Journal of Business Management*. 6(27): 8065-8070.

MALAN, G., 2016. *The impact of the economy on the SA ICT industry*. [Online]. Available: http://www.biznisafrica.co.za/the-impact-of-the-economy-on-sa-ict-industry/. [Accessed 14 October 2016]

MANDIMIKA, N., 2010. *Volatility and the risk-return relationship on the South African equity market.* Unpublished Masters Thesis. Grahamstown: Dept of Economics, Rhodes University.

MANDIMIKA, N and CHINZARA, Z., 2012. Risk- return trade-off and behaviour of volatility on the South African stock market: Evidence from both aggregate and disaggregate data. *South African Journal of Economics,* 80(3): 345-366.

MANGANI, R., 2008. Modelling return volatility on the JSE Securities Exchange of South Africa. *African Finance Journal*, 10(1): 55-71.

MASOTE, M., 2013. Transformation slow in financial services. [Online]. Available: http://www.fin24.com/Companies/Financial-Services/Transformation-slow-in-financial-services-20131020. [Accessed 8 December 2016].

MAYER, N., 2013. Top performing sectors on the JSE. [Online]. Available: http://www.sharenet.co.za/marketviews/article/Top_Performing_Sectors_of_the_JSE/1877. [Accessed 18 October 2016].

MAYSAMI, R. C., HOWE, L. C and HAMZAH, M. A., 2004. Relationship between macroeconomic variables and stock market indices: Cointegration evidence from stock exchange of Singapore's All-S sector indices. *Journal Pengurusan.* 24: 47–77.

MERTON, R., 1973. An intertemporal capital asset pricing model. *Econometrica,* 41(3): 867-887.

MINING REVIEW AFRICA, 2015. *Weaker financial performance for SA mining sector for 2015.* [Online]. Available: https://www.miningreview.com/news/weak-financial-performance-for-sa-mining-sector-in-2015-says-pwc/. [Accessed 15 October 2015].

MUBARIK, F and JAVID, Y. A., 2009. Relationship between stock return, trading volume and volatility: Evidence from Pakistani stock market. *Asia Pacific Journal of Finance and Banking Research,* 3(3):1-17.

NATIONAL TREASURY DEPARTMENT, 2011. *A safer financial sector to serve South Africa better*. [Online]. Available: http://www.treasury.gov.za/twinpeaks/20131211%20-%20Item%202%20A%20safer%20financial%20sector%20to%20serve%20South%20Africa%20better.pdf. [Accessed: 11 October 2016].

NDWIGA, D and MURIU, P. W., 2016. Stock return and volatility in an emerging equity market. Evidence from Kenya. *European Scientific Journal,* 12(4):1857-7431.

NELSON, D. B., 1991. Conditional Heteroskedasticity in asset returns: A New Approach. *Econometrica*, 59 (2), 347-370.

NIYITEGEKA, O and TEWARI, D. D., 2013. Volatility clustering at the Johannesburg Stock Exchange: Investigation and analysis. *Mediterranean Journal of Social Sciences,* 4(14): 621-626.

OBERUC, R. E., 2011. *Dynamic portfolio theory and management: using active asset allocation to improve profits and reduce risk*. USA: McGraw-Hill.

PAAVOLA, M., 2006. Tests of the arbitrage pricing theory using macroeconomic variables in the Russian equity market. [Online] Available: http:// www.eurojournals.com/irjfe_22_04.pdf

PATTERSON, C. S., 1995. *Cost of capital: Theory and estimation*. Greenwood Publishing Group: Westport, CT.

PATTON, A. J and SHEPPARD, K., 2015. Good volatility, bad volatility: Signed jump and the persistence of volatility. *The Review of Economics and Statistics,* 97(6):683-697.

PETROFF, A., 2013. Investing in different industry sectors. [Online]. Available: http://www.morningstar.co.uk/uk/news/105772/investing-in-different-industry-sectors.aspx. [Accessed 8 December 2016].

PRAST, H., 2004. Investor Psychology: A behavioural explanation of six finance puzzles. *Research Series Supervision,* 64: 1- 25.

RANGEL, J. G., 2011. Macroeconomic news, announcements and stock market jump intensity dynamics. *Journal of Banking and Finance,* 35: 1263-1276.

ROSS, S. A., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory,* 13: 341−60.

ROLL, R and ROSS, S., 1984. The arbitrage pricing theory approach to strategic portfolio planning. *Financial Analysts Journal,* January-February: 14-26.

SAXTON, G.D and ANKER, A.E., 2013. The Aggregate Effects of Decentralized Knowledge Production: Financial Bloggers and Information Asymmetries in the Stock Market. *Journal of Communication,* 63: 1054-1069.

SHARPE, W., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance,* 19(3): 425 - 442.

SHI, Y., HO, K.Y and LIU, W.M., 2015. Public information arrival and stock return volatility: Evidence from news sentiment and Markov Regime Switching Approach. *International Review of Economics and Finance*, 30: 1-22.

SHLEIFER, A and SUMMERS, L. H., 1990. The noise trader approach to finance. *The Journal of Economics Perspective,* 4(2): 19 – 33.

SHLEIFER, A. and VISHNY, R. W., 1997. The limits of arbitrage. *Journal of Finance,* 52: 35 – 55.

SINHA, B., 2006. Modelling Stock Market Volatility in Emerging Markets: Evidence from India. [Online] Available: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=954189. [Accessed 18 July 2016].

SINHA, R., 2015. Impact of leverage on stock price volatility reference to automobile sector. [Online] Available: http://www.ifsmrc.org/?q=journals/management/volume3/issue6/Automobile%20sector . [Accessed 1 May 2016]

SOROKA, S. N., 2006. Good news and Bad news: Asymmetric Responses to Economic Information. *The Journal of Politics*, 68(2): 372-385.

SUBRAHMANYAM, A., 2007. Behavioural Finance: A Review and Synthesis. *European Financial Management* 14 (1): 12-29.

SULEMAN, M. T., 2012. Stock market reaction to good and bad political news. *Asian Journal of Finance and Accounting,* 4(1): 299-312.

SYRIOPOULOS, T., MAKRAM, B and BOUBAKER, A., 2015.Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis,* 39:7-18.

TAKAENDESA, P., TSHEOLE, T and AZIAKPONO, M. J., 2006. Real exchange rate volatility and its effect on trade flows: New evidence from South Africa. *Studies in Economics and Econometrics*, 30 (3), 79-97.

TVERSKY, A and KAHNEMAN, D., 1974. Judgement under uncertainty: Heuristics and biases. *Science*, 185: 1124 -1131.

UYGUR, U and TAS, O., 2014. The impact of investor sentiment on different economic sectors: Evidence from Istanbul Stock Exchange. *Borsa Istanbul Review,* 14(4): 236-241.

VAN RENSBURG, P., 1997. Investment basics: XXXIV. The arbitrage pricing theory. *Investment Analyst Journal,* 46: 60 – 63.

VAN WYK, K., 2015. Regulation and Ethics of the South African Financial Markets. *South African Institute of Financial Markets (SAIFM)*. 1-152.

VARIAN, H. R., 2010. *Intermediate Macroeconomics: A modern approach (8e)*. Norton & Company: New York, United States of America.

VENDEIRO, N., 2015. Rebasing of oil and gas index (J500). [Online]. Available: https://www.jse.co.za/content/JSEHotlinesItems/JSE%20Service%20Hotline%209415%20Market%20Data%20-%20Rebasing%20of%20Oil%20and%20Gas%20Index%20(J500).pdf. South Africa: Johannesburg Stock Exchange, [Accessed 13 September 2016].

WU, G, 2001. The determinants of asymmetric volatility. *The Review of Financial Studies,* 14: 837-859.

YARTEY, C. A and ADJASI, C. K., 2007. Stock markets development in Sub-Saharan Africa: Critical Issues and Challenges. *International Monetary Fund,* 1-33.

YELTEN, E. S., 2003. Real effects of movements in normal exchange rates: application to the Asian crisis. *Journal of Applied Economics*, 6: 341–59.

ZAKOIAN, J. M., 1993. Threshold Arch Models and Asymmetries in Volatility. *Journal of Applied Econometrics*, 8 (1), 31-49.

APPENDICES

APPENDIX A: Tables

Table A1 : ***ICB Sectoral Classification***

Index	Index Code	Sample Period
Basic Materials		
FTSE/JSE Basic materials	J510	02/01/1997-17/08/2016
Consumer Goods		
FTSE/JSE Consumer goods	J530	02/01/1997-17/08/2016
Consumer Services		
FTSE/JSE Consumer services	J550	02/01/1997-17/08/2016
Financials		
FTSE/JSE Financials	J580	02/01/1997-17/08/2016
Health Care		
FTSE/JSE Health care	J540	02/01/1997-17/08/2016
Industrials		
FTSE/JSE Industrials	J520	02/01/1997-17/08/2016
Oil and Gas		
FTSE/JSE Oil & gas	J500	02/01/1997-23/12/2015
Technology		
FTSE/JSE Technology	J590	02/01/1997-17/08/2016
Telecommunications		
FTSE/JSE Telecommunication	J560	02/01/1997-17/08/2016
Benchmark		
FTSE/JSE Mid cap	J201	02/01/2002-17/08/2016
FTSE/JSE Small cap	J202	02/01/2002-17/08/2016
FTSE/JSE All share	J203	02/01/1997-17/08/2016

Table A2: ***Stationarity tests***

	Pre-crisis period		**During crisis**		**Post-crisis**		**Whole sample**	
Sectors	**ADF**	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**
Basic materials	-47.2498*	0.2057	-17.6619*	0.2245	-31.7103*	0.0759	-64.7401*	0.167
Consumer Goods	-50.1018*	0.0659	-18.9913*	0.1208	-42.7627*	0.2071	-67.5065*	0.0435
Consumer Services	-45.0218*	0.2591	-17.6328*	0.1244	-41.9261*	0.0507	-64.3066*	0.3504
Health Care	-48.9433*	0.1778	-17.1838*	0.2012	-42.8086*	0.2286	-66.1456*	0.219
Financials	-45.5703*	0.0873	-17.6298*	0.2227	-31.6443*	0.0843	-63.1229*	0.043
Technology	-47.3124*	0.2263	-17.8534*	0.2721	-41.0319*	0.2396	-63.7454*	0.3089
Telecommunications	-47.8263*	0.1410	-15.5612*	0.1169	-33.6741*	0.2375	-50.5699*	0.1268
Industrials	-48.8230*	0.2621	-17.6314*	0.1970	-42.1333*	0.0884	-66.0006*	0.0765
Oil and Gas	-47.5163*	0.1114	-19.3621*	0.1028	-23.2072*	0.1628	-61.3063*	0.0561
Benchmark Indices								
Allshare	-48.8968*	0.1971	-17.8631*	0.2774	-31.8764*	0.0886	-66.1624*	0.0441
Small Cap	-17.4821*	0.2527	-14.1812*	0.2872	-37.2673*	0.1442	-28.9878*	0.3618
Mid Cap	-30.7887*	0.1344	-15.4475*	0.2074	-39.4124*	0.1234	-51.7150*	0.1708

Source: Author's estimates

*Note: * - Observed t-statistic values are significant at the 1% significant level*

For the KPSS test all the LM statistics are insignificant therefore we fail to reject the null hypothesis of a stationary series.

Descriptive Statistics

Table A3.1*: **Whole sample period***

Sectors	Mean	Median	Max.	Min	Std. Dev	Skewness	Kurtosis	Jq-Bera
Basic Materials	0.0302	0.0474	11.1619	-11.8114	1.7826	-0.0087	6.9129	3138.815*
Financials	0.0366	0.0503	8.1137	-13.3122	1.3247	-0.4444	9.5977	9081.848*
Consumer Goods	0.0666	0.0316	14.2121	-12.3441	1.6410	0.2269	8.1944	5572.33*
Consumer Services	0.0590	0.0928	7.4953	-10.3697	1.2826	-0.3976	7.0016	3411.515*
Industrials	0.0449	0.0647	7.6880	-13.6171	1.2547	-0.4977	9.7627	9576.554*
Technology	0.0177	0.0296	15.1134	-20.7987	1.9526	-0.6044	14.2021	26019.09*
Telecommunications	0.0514	0.0712	19.6469	-18.6872	2.1220	-0.0585	9.0915	7606.564*
Oil and Gas	0.0619	0.0285	31.0779	-17.1851	2.0540	0.9392	22.0960	71136.18*
Health Care	0.0587	0.0698	11.1142	-14.3960	1.3695	-0.2633	9.0792	7631.33*
Benchmark indices								
All-Share	0.0438	0.0687	7.2680	-12.6256	1.2603	-0.4527	8.7237	6881.109*
Small Cap	0.0634	0.0933	6.2483	-4.5861	0.5901	-0.7640	12.0046	12696.92*
Mid Cap	0.0630	0.0902	4.7117	-5.6326	0.7991	-0.5271	6.8399	2413.39*

Source: Author's estimates
*Note: * - 1% significant level*

Table A3.2:***Pre-crisis period***

Sectors	Mean	Median	Max.	Min	Std. Dev	Skewness	Kurtosis	Jq-Bera
Basic Materials	0.0699	0.079	10.4963	-8.2620	1.6255	-0.004451	5.893755	980.0951*
Financials	0.0389	0.0421	8.1137	-13.3121	1.3680	-0.610744	10.95819	7587.196*
Consumer Goods	0.0626	0.0037	9.6180	-12.3441	1.8709	0.120574	6.47739	1422.102*
Consumer Services	0.0366	0.0808	6.7464	-10.3697	1.1794	-0.955449	10.44173	6909.081*
Industrials	0.0590	0.0825	7.6880	-13.6171	1.3267	-0.709824	11.25235	8206.576*
Technology	-0.0165	0	14.6737	-20.7987	2.2449	-0.681095	11.77174	9222.773*
Telecommunications	0.0830	0.0894	19.6469	-18.6872	2.1976	-0.028146	9.293987	4636.892*
Oil and Gas	0.0719	0.0438	8.2584	-11.8668	1.7683	-0.082738	6.022114	1072.167*
Health Care	0.0384	0.0496	11.1142	-14.3960	1.4652	-0.358819	10.3991	6467.918*
Benchmark indices								
All-Share	0.0576	0.0799	7.2680	-12.6256	1.2597	-0.681901	10.19811	6281.946*
Small Cap	0.1152	0.1482	1.7889	-3.9550	0.5379	-1.140569	8.570303	2272.039*
Mid Cap	0.0945	0.1148	2.9577	-3.9868	0.6605	-0.780651	6.57664	955.049*

Source: Author's estimates
*Note: * - 1% significant level*

Table A3.3:***During- crisis period***

Sectors	Mean	Median	Max.	Min	Std. Dev	Skewness	Kurtosis	Jq-Bera
Basic Materials	-0.113988	-0.284319	11.16194	-11.81142	3.3033	0.0507	4.297174	25.67622*
Financials	-0.045147	-0.139284	7.149495	-6.653394	2.0179	0.2033	3.702598	9.99506*
Consumer Goods	0.026129	-0.021254	14.21213	-7.438639	1.9354	1.0276	10.65131	951.9575*
Consumer Services	0.031242	-0.119763	6.407912	-5.533203	1.6601	0.1770	3.501366	5.713857*
Industrials	-0.063993	-0.092217	6.984469	-5.634925	1.6637	0.0838	4.328378	27.18934*
Technology	-0.035143	-0.0188	10.20728	-13.62279	2.3921	-0.3495	7.910043	373.0578*
Telecommunications	0.003244	-0.162422	13.46524	-10.98515	3.0847	0.322	4.796642	55.24698*
Oil and Gas	-0.092321	0.021147	13.46524	-10.98515	3.0847	0.322	4.796642	55.24698*
Health Care	0.078073	0.07056	6.040649	-5.185172	1.7311	0.0741	3.607752	5.935202*
Benchmark indices								
All-Share	-0.060224	-0.053986	6.833971	-7.580684	2.1344	0.0131	3.894423	12.14364*
Small Cap	-0.109558	-0.064911	2.940637	-4.586148	0.8529	-0.9035	7.683936	382.2677*
Mid Cap	-0.049601	-0.00636	4.711686	-5.632579	1.3515	-0.2499	4.34329	55.24698*

Source: Author's estimates

*Note: * - 1% significant level*

Table A3.4: ***Post-crisis period***

Sectors	Mean	Median	Max.	Min	Std. Dev	Skewne ss	Kurtosis	Jq-Bera
Basic Materials	-0.0035	0.011607	7.428177	-6.154759	1.5576	0.0622	4.128775	93.87118*
Financials	0.0498	0.087624	5.335931	-8.407446	1.0419	-0.5300	7.592153	1614.944*
Consumer Goods	0.0813	0.092916	8.815879	-5.478945	1.0850	0.0916	6.525213	906.5157*
Consumer Services	0.1007	0.142012	7.495337	-5.453152	1.3498	-0.0166	4.565312	178.3325*
Industrials	0.0449	0.051171	5.462353	-5.715617	1.0130	-0.1112	5.100769	324.6589*
Technology	0.0838	0.056508	15.11339	-8.447789	1.1993	0.8405	21.57998	25320.03*
Telecommunications	0.0106	0.054423	9.084275	-15.91411	1.7132	-0.6270	9.33715	3034.261*
Oil and Gas	0.0809	0.00294	31.07786	-17.18506	2.0881	2.7867	52.11495	149043.7*
Health Care	0.0874	0.087506	4.148652	-5.036968	1.0984	-0.0747	4.140789	96.3015*
Benchmark indices								
All-Share	0.0432	0.072543	4.233228	-3.693919	0.9861	-0.2034	4.230544	122.1271*
Small Cap	0.0550	0.069459	6.2483	-3.868031	0.5591	-0.0575	15.06271	10817.15*
Mid Cap	0.0595	0.082522	4.247923	-3.742799	0.7515	-0.3265	5.17528	383.4357*

Source: Author's estimates

*Note: * - 1% significant level*

Autocorrelation and ARCH effects results

Table A4.1: ***Whole sample period***

SECTOR	ARMA (p,q)	LM TEST	ARCH-LM TEST
Basic materials	(0, 1)	0.1493 [0.6992]	194.4218*
Consumer Goods	(0,1)	0.4111[0.5214]	228.0283*
Consumer Services	(0, 1)	6.74E-05 [0.9934]	433.8398*
Health Care	(0, 1)	0.5774[0.4473]	361.9013*
Financials	(0, 1)	0.0633[0.8013]	568.5369*
Technology	(1,1)	2.2456[0.1340]	549.1210*
Telecommunication	(1,(1, 2))	3.96E-05[0.9950]	303.4112*
Industrial	(1, 1)	1.7431[0.1867]	534.3303*
Oil and Gas	(0,1)	0.2808[0.5962]	854.0331*
Benchmark Indices			
Allshare	(0, 1)	0.5616[0.4536]	483.4768*
Small Cap	(1, (1,2))	1.7004[0.1922]	265.1467*
Mid Cap	(1, 0)	0.4117 [0.5211]	284.4890*

Source: Author's estimates
*Note: * - Statistically significant at the 1% level.*
[ ] – P-values of the observed LM statistic

Table A4.2**: Pre- crisis**

SECTOR	ARMA (p,q)	LM TEST	ARCH-LM TEST
Basic materials	((1, 2),0)	0.0016[0.9685]	72.8714*
Consumer Goods	(0,1)	0.1046[0.7463]	167.0704*
Consumer Services	(1, 1)	2.4229[0.1196]	430.1911*
Health Care	(0, 1)	0.4245[0.5147]	228.6457*
Financials	(1, 0)	0.5244[0.4690]	424.1285*
Technology	(1,1)	1.3476[0.2457]	377.1449*
Telecommunication	(0,1)	0.2074[0.6488]	214.3114*
Industrial	(1, 0)	0.1839[0.6681]	382.9869*
Oil and Gas	(1,0)	0.9877[0.3203]	146.726*
Benchmark Indices			
Allshare	(0,(1, 2)	0.0082[0.9279]	387.1892*
Small Cap	(1, 1)	1.6773[0.1953]	19.386*
Mid Cap	(1, 0)	0.1295[0.7190]	75.195*

Source: Author's estimates
*Note: * - Statistically significant at the 1% level.*
[ ] – P-values of the observed LM statistic

Table A4.3: **During crisis**

Sectors	ARMA (p,q)	LM TEST	ARCH-LM TEST
Basic materials	((1, 2),(1,2))	0.0262[0.8713]	7.8699*
Consumer Goods	***(0, 0)***	***0.0021[0.9639]***	***0.19499***
Consumer Services	(0, 1)	1.3798[0.2401]	4.8259**
Health Care	(1, 1)	0.7556[0.3847]	6.2037**
Financials	(0, 2)	2.0768[0.1496]	3.9875**
Technology	(1, 1)	0.1667[0.6830]	6.3263**
Telecommunication	(1,(1, 2))	0.1977[0.6566]	16.4235**
Industrial	(1, 1)	0.0002[0.9891]	16.0503*
Oil and Gas	(1, 1)	0.8293[0.3625]	11.0463*
Benchmark Indices			
Allshare	(3, 0)	1.0411[0.3076]	3.4199**
Small Cap	(1, 0)	0.3112[0.5769]	3.660606**
Mid Cap	(1, 0)	0.0406[0.8403]	20.6531*

Source: Author's estimates

*Note: *, **,***- Statistically significant at the 1%, 5% and 10% level.*

[ ] – P-values of the observed LM statistic

For Consumer goods, no proper ARMA structure was found and it was regressed on a constant

Table A4.4: **Post Crisis**

Sectors	ARMA (p,q)	LM TEST	ARCH-LM TEST
Basic materials	(2, 2)	3.5397[0.1704]	9.7301*
Consumer Goods	(1, 1)	0.0006[0.9807]	11.7062*
Consumer Services	(1, 1)	0.8463[0.3576]	35.3258*
Health Care	(1, 1)	0.8579[0.3543]	56.0394*
Financials	(1, 1)	1.7031[0.1919]	206.4336*
Technology	(3, 3)	1.6172[0.6555]	9.2928*
Telecommunication	(1, 1)	0.0774[0.7808]	6.8666*
Industrial	(1, 1)	0.1738[0.6768]	0.6768*
Oil and Gas	(0, 1)	0.1909[0.6621]	263.8067*
Benchmark Indices			
Allshare	(2, 2)	0.2800[0.8694]	29.70585*
Small Cap	(1, 1)	0.6232[0.4299]	208.681*
Mid Cap	(0, 1)	1.7129[0.1906]	104.097*

Source: Author's estimates

*Note: * - Statistically significant at the 1% level.*

[ ] – P-values of the observed LM statistic

Univariate GARCH models

Table A5.1: ***EGARCH (p, r, q) for the whole sample period***

Sectors	ω	α_1	β	γ	α_2	$\alpha_1 + \alpha_2 + \beta$
Basic materials	0.8578	0.3322	N/A	-0.0683*	N/A	0.3322
Consumer goods	-0.1075	0.1952	0.9861	-0.0565*	-0.0397	1.1416+
Consumer services	-0.1641	0.3933	N/A	-0.0911*	0.3365	0.7298
Financials	-0.1448	0.2719	0.9780	-0.0771*	-0.0777	1.1722+
Health Care	-0.0917	0.3008	0.9867	-0.0264*	-0.1724	1.1151+
Industrials	-0.1303	0.2513	0.9723	-0.0690*	-0.0746	1.1491+
Technology	-0.0729	0.3667	0.9928	-0.0310*	-0.2564	1.1032+
Telecommunications	-0.0915	0.3195	0.9859	-0.0242*	-0.1749	1.1305+
Benchmark indices						
Allshare	-0.1386	0.1830	0.9770	-0.0842*	N/A	1.1600
Small Cap	-0.1710	0.3272	0.9640	-0.0689*	-0.1643	1.1269+
Mid Cap	-0.1365	0.2065	0.9773	-0.0518*	-0.0510	1.1328+

Source: Author's estimates
,,*** means that the coefficient is statistically significant at 1%, 5% and 10% level.*
+ marks the summation of $\alpha_1 + \alpha_2 + \beta$ which is a condition of stationarity of the GARCH model. For sectors not marked by the +, stationarity condition is $\alpha_1 + \beta$.

Table A5.2: ***EGARCH (p, r, q) for the Oil and Gas Sector***

Sector	ω	α_1	α_2	α_3	α_4	α_5	α_6	β	γ
Oil & Gas	-0.2062	0.3526	0.3229	0.3329	0.2305	0.2299	0.1938	N/A	0.0309**

, **, * means that the coefficient is statistically significant at 1%, 5% and 10% level*

Table A5.3: ***Pre-crisis EGARCH (p,r,q)***

Sectors	ω	α_1	β	γ	α_2	$\alpha_1 + \alpha_2 + \beta$
Basic materials	-0.1456	0.2449	0.9535	-0.0463	n/a	1.1984
Consumer goods	-0.1096	0.2419	0.9782	-0.0606	-0.0655	1.1546
Consumer services	-0.1352	0.3030	0.9765	-0.0714	-0.1275	1.1520
Financials	-0.1388	0.3437	0.9779	-0.0738	-0.1531	1.1684
Health Care	-0.0812	0.3330	0.9866	-0.0205	-0.2139	1.1057
Industrials	-0.1239	0.2996	0.9677	-0.0656	-0.1226	1.1447
Technology	-0.0551	0.4331	0.9907	-0.0296	-0.3408	1.0830
Telecommunications	-0.0998	0.3363	0.9765	-0.0246	-0.1618	1.1510
Oil and Gas	-0.0925	0.2420	0.9749	-0.0281	-0.0844	1.1325
Benchmark indices						
Allshare	-0.1634	0.2220	0.9653	-0.0835	n/a	1.1873
Small Cap	-0.3887	0.2463	0.8566	-0.1226	n/a	1.1029
Mid Cap	-0.2875	0.2260	0.8891	-0.0915	n/a	1.1151

Source: Author's estimates
,,*** means that the coefficient is statistically significant at 1%, 5% and 10% level.*

+ marks the summation of α_1 +α_2 + β which is a condition of stationarity of the GARCH model. For sectors not marked by the +, stationarity condition is α_1 + β.

Table A5.4: ***During crisis EGARCH (p,r,q)***

Sectors	**ω**	**α₁**	**β**	**γ**	**α₂**	**α₁ + α₂ + β**
Basic materials	0.0564	-0.2101	0.9930	-0.1096	0.1586	0.9415
Consumer goods	n/a	n/a	n/a	n/a	n/a	n/a
Consumer services	-0.0662	0.1000	0.9845	-0.0938	n/a	1.0845
Financials	-0.1606	0.2359	0.9764	-0.0623	n/a	1.2123
Health Care	*-0.0507*	0.2649	0.8519	*-0.0681*	n/a	1.1169
Industrials	-0.0985	-0.1528	0.9634	-0.1443	0.3184	
Technology	-0.0599	0.3942	0.9876	-0.0712	-0.2834	1.0984
Telecommunications	*-0.0584*	0.1581	0.9677	-0.1123	n/a	
Oil and Gas	0.1046	-0.0676	0.9823	-0.1390	n/a	0.9147
Benchmark indices						
Allshare	0.0620	-0.0655	0.9922	-0.1060	n/a	0.9266
Small Cap	-0.1335	0.1164	0.9317	-0.1424	n/a	1.0481
Mid Cap	-0.0988	0.1436	0.9658	-0.0981	n/a	1.1094

Source: Author's estimates
,,*** means that the coefficient is statistically significant at 1%, 5% and 10% level. Values in italics are insignificant*
+ marks the summation of α_1 +α_2 + β which is a condition of stationarity of the GARCH model. For sectors not marked by the +, stationarity condition is α_1 + β.

Table A5.5: ***Post-crisis EGARCH (p,r,q)***

Sectors	**ω**	**α₁**	**β**	**γ**	**α₂**	**α₁ + α₂ + β**
Basic materials	-0.0269	0.0392	0.9955	-0.0501	n/a	1.0347
Consumer goods	-0.0825	0.1126	0.9677	-0.0567	n/a	1.0802
Consumer services	-0.0730	0.2520	0.9807	-0.0639	-0.1454	1.2327
Financials	-0.0965	0.1207	0.9692	-0.1129	n/a	1.0899
Health Care	-0.1377	0.1791	0.9649	-0.0534	n/a	1.1440
Industrials	-0.1063	0.1293	0.9697	-0.0931	n/a	1.0989
Technology	-0.0885	0.2530	0.9915	-0.0409	-0.1244	1.1201
Telecommunications	-0.0297	0.0494	0.9917	-0.0434	n/a	1.0411
Oil and Gas	-0.1748	0.2609	0.9754	0.0413	n/a	1.2363
Bechmark indices						
Allshare	-0.0777	0.0896	0.9644	-0.1363	n/a	1.0540
Small Cap	-0.1385	0.3500	0.9813	-0.0239	-0.2050	1.1263
Mid Cap	-0.1061	0.1841	0.9845	-0.0528	*-0.0622*	1.1064

Source: Author's estimates
,,*** means that the coefficient is statistically significant at 1%, 5% and 10% level. Values in italics are insignificant*
+ marks the summation of α_1 +α_2 + β which is a condition of stationarity of the GARCH model. For sectors not marked by the +, stationarity condition is α_1 + β.

Table A6.1: ***The Differential Impact of Good and Bad news for the whole sample period***

	TGARCH			EGARCH		
Sectors	**Good news (α_1)**	**Bad news ($\alpha_1 + \gamma$)**	**Difference (%)**	**Good news ($\alpha_1 + \gamma$)**	**Bad news ($-\alpha_1 + \gamma$)**	**Difference (%)**
Basic materials	0.1071	0.2849	166.01	0.2639	-0.4005	-251.76
Consumer goods	0.0448	0.1132	152.68	0.1387	-0.2517	-281.47
Consumer services	0.1965	0.3741	90.38	0.3933	-0.4844	-223.16
Financials	0.0574	0.1613	181.01	0.1948	-0.3490	-279.16
Health Care	0.2585	0.3169	22.59	0.2744	-0.3272	-219.24
Industrials	0.0488	0.1506	208.61	0.1824	-0.3203	-275.60
Technology	0.3899	0.5716	46.60	0.3358	-0.3977	-218.43
Telecommunications	0.2230	0.3853	72.78	0.2953	-0.3436	-216.36
Oil and Gas	0.3676	0.2956	-19.59	0.3835	0.3218	-16.09
Benchmark Indices						
All-share	0.0391	0.1422	263.68	0.0988	-0.2672	-370.45
Small Cap	0.2425	0.3470	43.09	0.2583	-0.3961	-253.35
Mid Cap	0.0485	0.1288	169.57	0.1547	-0.2583	-266.97

Source: Author's estimates

Table A6.2: ***EGARCH differential impact***

	Pre-crisis			During-crisis			Post-crisis		
Sectors	**Good news ($\alpha1 + \gamma$)**	**Bad news ($-\alpha1 + \gamma$)**	**Difference (%)**	**Good news ($\alpha1 + \gamma$)**	**Bad news ($-\alpha1 + \gamma$)**	**Difference (%)**	**Good news ($\alpha1 + \gamma$)**	**Bad news ($-\alpha1 + \gamma$)**	**Difference (%)**
Basic materials	0.1985	-0.2912	-246.68	-0.3197	0.1006	-131.46	-0.0110	-0.0893	713.35
Consumer goods	0.1813	-0.3025	-266.83	n/a	n/a	n/a	0.0558	-0.1693	-403.29
Consumer services	0.2316	-0.3744	-261.65	0.0062	-0.1938	-3242.65	0.1881	-0.3159	-267.91
Financials	0.2699	-0.4174	-254.66	0.1736	-0.2982	-271.76	0.0078	-0.2336	-3081.14
Health Care	0.3125	-0.3534	-213.10	0.1969	-0.3330	-269.14	0.1257	-0.2326	-285.02
Industrials	0.2340	-0.3652	-256.10	-0.2971	0.0138	-104.64	0.0362	-0.2223	-714.34
Technology	0.4035	-0.4627	-214.69	0.3230	-0.4654	-244.07	0.2121	-0.2939	-238.55
Telecommunications	0.3117	-0.3610	-215.79	0.0458	-0.2705	-690.68	0.0060	-0.0929	-1652.70
Oil and Gas	0.2139	-0.2700	-226.23	-0.2066	-0.0714	-65.43	0.3022	-0.2196	-172.66
Benchmark indices									
Allshare	0.1384	-0.3055	-320.68	-0.1715	-0.0404	-76.43	-0.0467	-0.2259	383.70
Small Cap	0.1236	-0.3689	-398.42	-0.0260	-0.2588	895.98	0.3261	-0.3740	-214.66
Mid Cap	0.1345	-0.3175	-335.99	0.0455	-0.2417	-630.75	0.1313	-0.2369	-280.39

Source: Author's estimates

Table A7.1: ***ARCH-LM Test (Diagnostic checks)***

	Pre-crisis		During crisis		Post-crisis	
Sectors	**TGARCH**	**EGARCH**	**TGARCH**	**EGARCH**	**TGARCH**	**EGARCH**
Basic Materials	2.3726[0.1235]	2.5322[0.1115]	0.1686[0.6814]	0.9479[0.3302]	0.1305[0.7179]	0.1848[0.6673]
Consumer goods	1.4159[0.2341]	0.9790[0.3224]	n/a	n/a	0.1813[0.6702]	0.0813[0.7756]
Consumer Services	0.9118[0.3396]	0.7241[0.3948]	0.1561[0.6928]	0.1330[0.7154]	0.4703[0.4929]	0.0948[0.7581]
Financials	2.0211[0.1551]	0.4395[0.4932]	0.1776[0.6735]	0.1968[0.6573]	0.0107[0.9175]	0.9264[0.3358]
Health Care	0.1544[0.6944]	2.3152[0.1218]	0.0264[0.8709]	0.0083[0.9275]	0.0566[0.8120]	0.7243[0.3948]
Industrials	2.3643[0.1241]	1.6460[0.1995]	0.2202[0.6389]	0.2922[0.5888]	0.0010[0.9742]	0.0471[0.8281]
Technology	0.2515[0.6160]	0.1732[0.6773]	1.3297[0.2489]	0.0044[0.9472]	0.0083[0.9276]	0.2980[0.5851]
Telecommunications	0.6084[0.4354]	0.7641[0.3821]	0.2988[0.5846]	0.4516[0.5016]	1.0162[0.3134]	1.6889[0.1937]
Oil and Gas	1.9611[0.1614]	2.2295[0.1354]	0.3148[0.5748]	0.2430[0.6221]	0.6927[0.4053]	*12.4380[0.000]*
Benchmark indices						
All-share	0.3529[0.5525]	0.0884[0.7662]	0.1291[0.7194]	1.3159[0.2513]	1.4508[0.2284]	1.4787[0.2240]
Small Cap	0.0412[0.8392]	0.0519[0.8198]	0.2737[0.6008]	0.6507[0.4199]	0.6048[0.4367]	2.0982[0.1475]
Mid Cap	1.2599[0.2886]	2.6188[0.1056]	2.5509[0.1102]	2.2902[0.1302]	2.2684[0.1320]	0.8793[0.3484]

Source: Author’s estimates

[], denotes the p-values of the observed LM statistic. The null hypothesis of the ARCH LM test is no ARCH effects.

The Arch LM test for all sectors and indices (in all periods) show that they are insignificant therefore the null hypothesis will not be rejected which suggest that for the TGARCH, all volatility is captured. For the EGARCH similar result for sectors and indices except the Oil and Gas which showed the presence of ARCH effects during the crisis period.

Table A7.2: ***ARCH-LM test for the whole sample (Diagnostic Checks)***

	Whole sample	
Sectors	**TGARCH**	**EGARCH**
Basic Materials	2.2619[0.1326]	1.9267[0.1651]
Consumer Goods	1.0801[0.2987]	1.6402[0.2003]
Consumer Services	1.7707[0.1896]	1.3127[0.2519]
Financials	2.6604[0.1029]	1.3139[0.2517]
Health Care	0.4569[0.4991]	2.6838[0.1014]
Industrials	2.0114[0.1561]	2.3670[0.1239]
Technology	0.7017[0.4022]	0.5371[0.4636]
Telecommunications	1.6803[0.1949]	0.7940[0.3729]
Oil and Gas	1.1317[0.2874]	2.6115[0.1061]
Benchmark indices		
All-share	0.9461[0.3307]	0.3623[0.5472]
Small Cap	0.1561[0.6928]	1.8953[0.1686]
Mid Cap	1.0561[0.3041]	1.1942[0.2745]

Source: Author's estimates

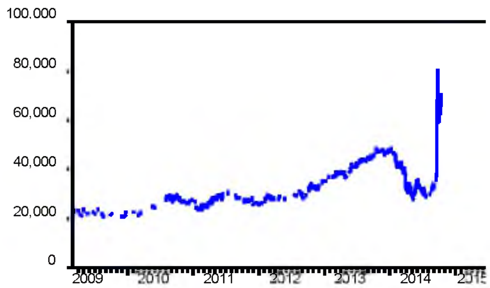
[], denotes the p-values of the observed LM statistic. The null hypothesis of the ARCH LM test is no ARCH effects.

The Arch LM test for all sectors and indices (in all periods) show that they are insignificant therefore the null hypothesis will not be rejected which suggest that for the TGARCH, all volatility is captured.

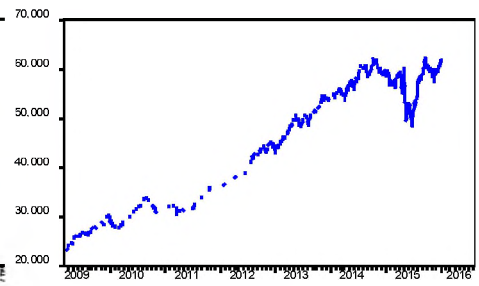
APPENDIX B: Graphs

APPENDIX B1: Whole Sample Period-Level Series

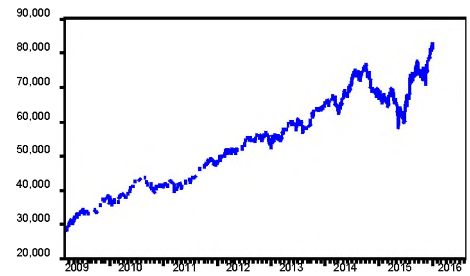
Oil and Gas



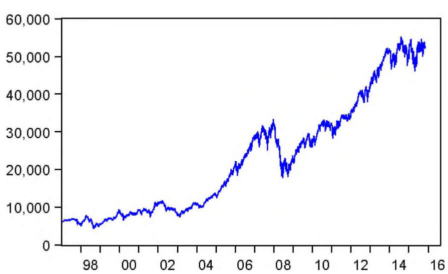
Small Cap



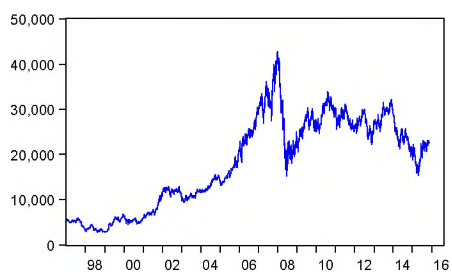
Mid Cap



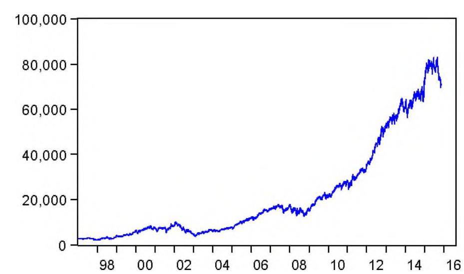
ALSI



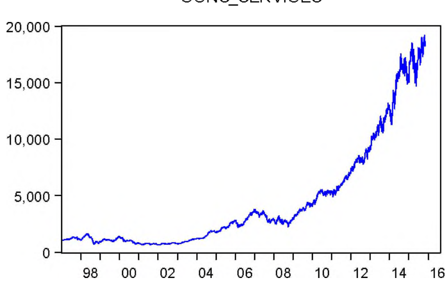
B_MATERIAL



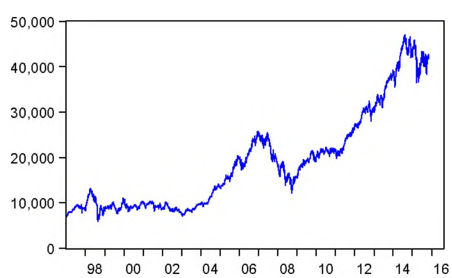
CONS_GOODS



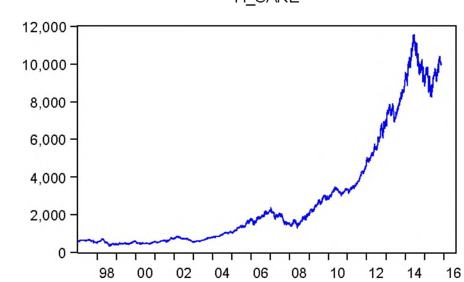
CONS_SERVICES



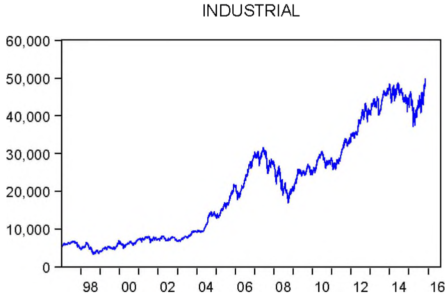
FINANCIALS



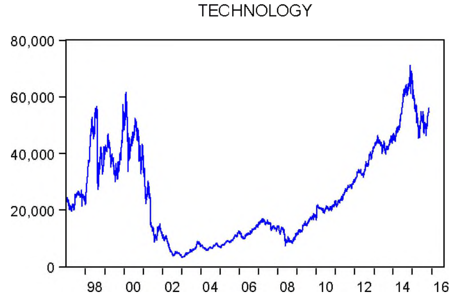
H_CARE



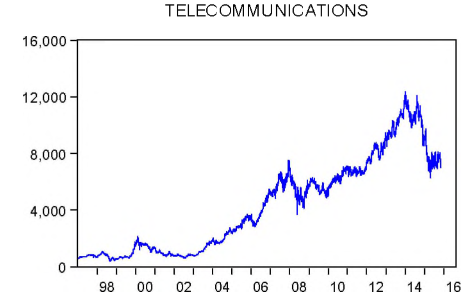
INDUSTRIAL



TECHNOLOGY

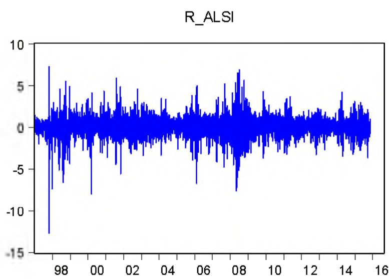


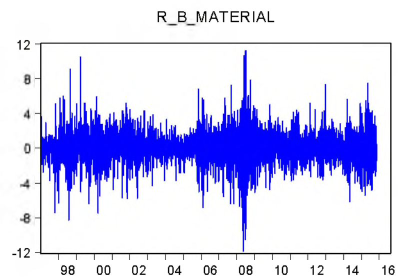
TELECOMMUNICATIONS

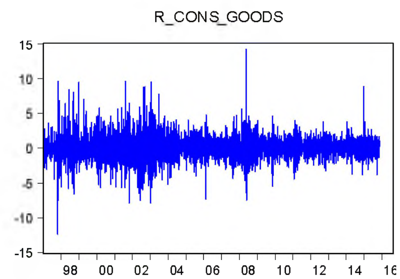


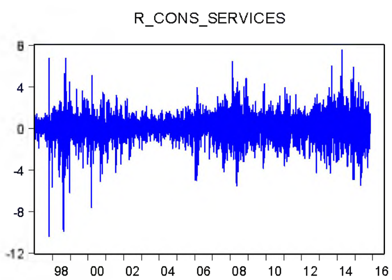
APPENDIX B2: RETURN SERIES

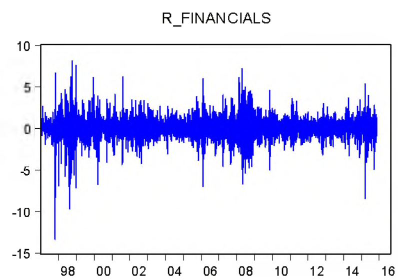
Whole Sample Period

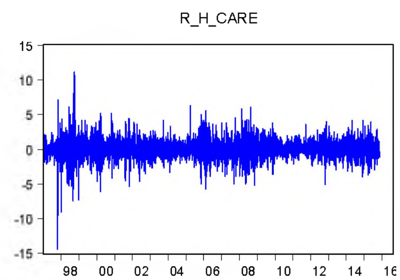


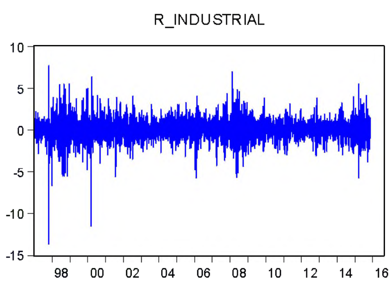


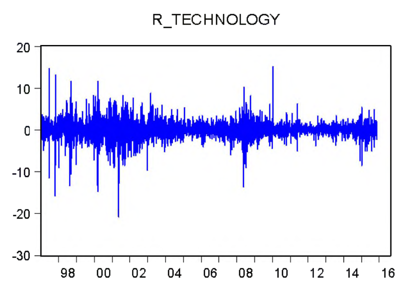


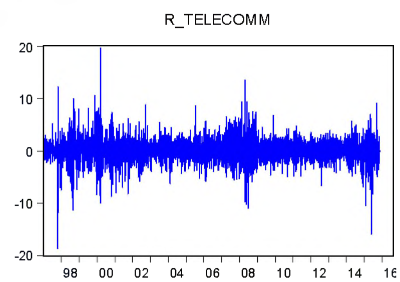


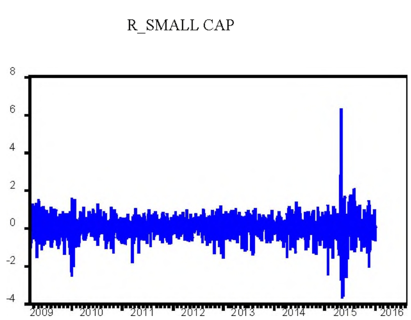


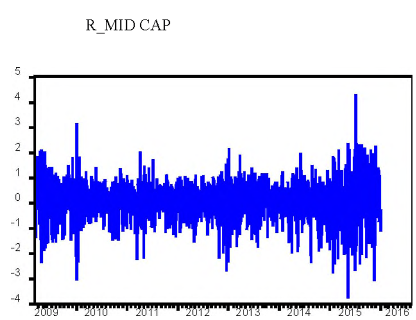


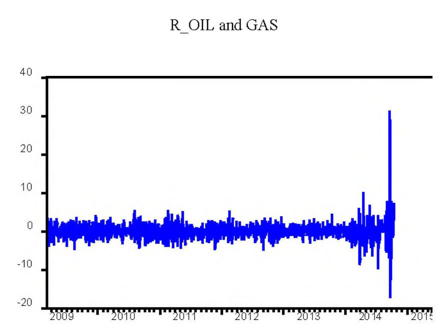




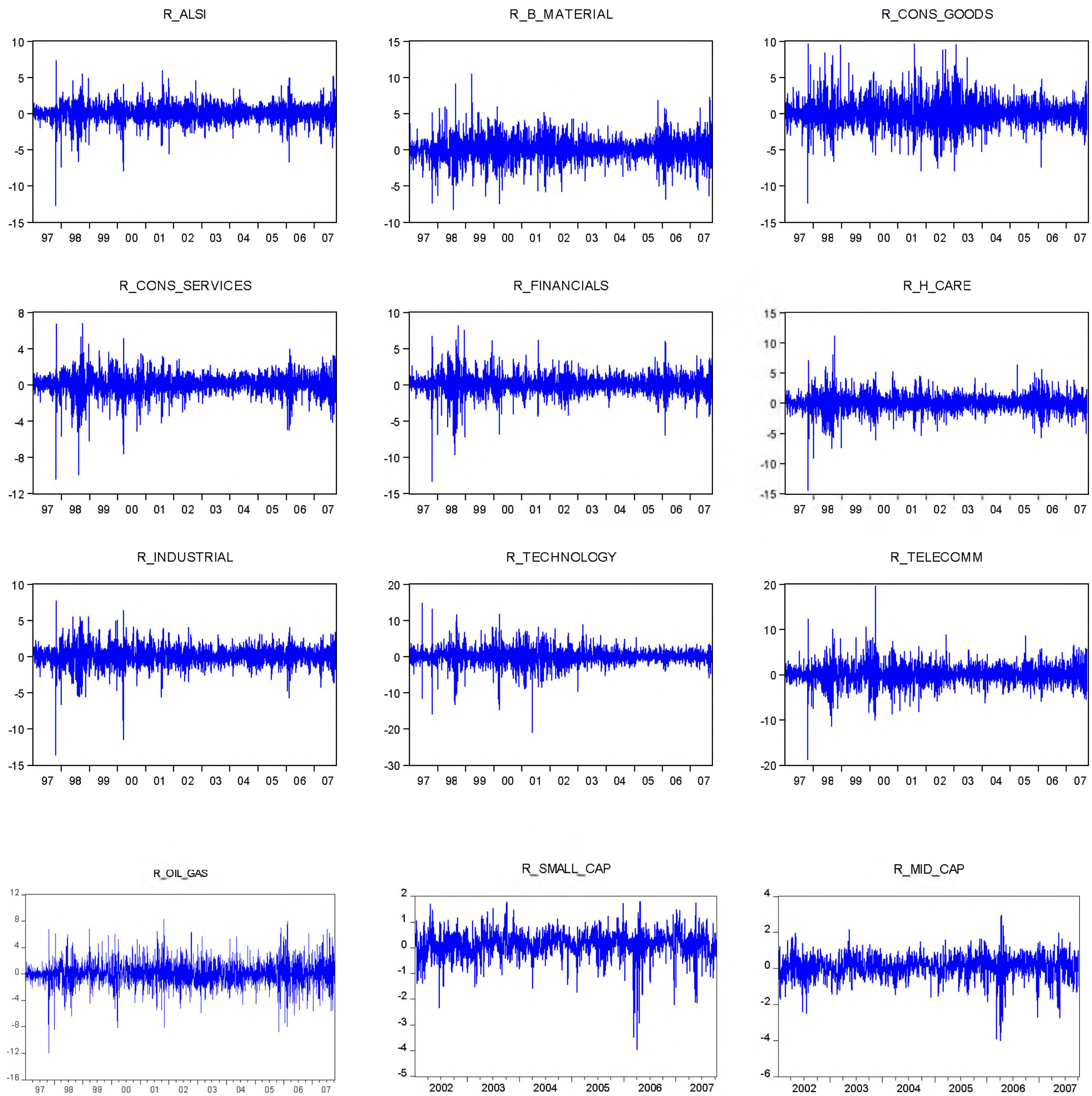




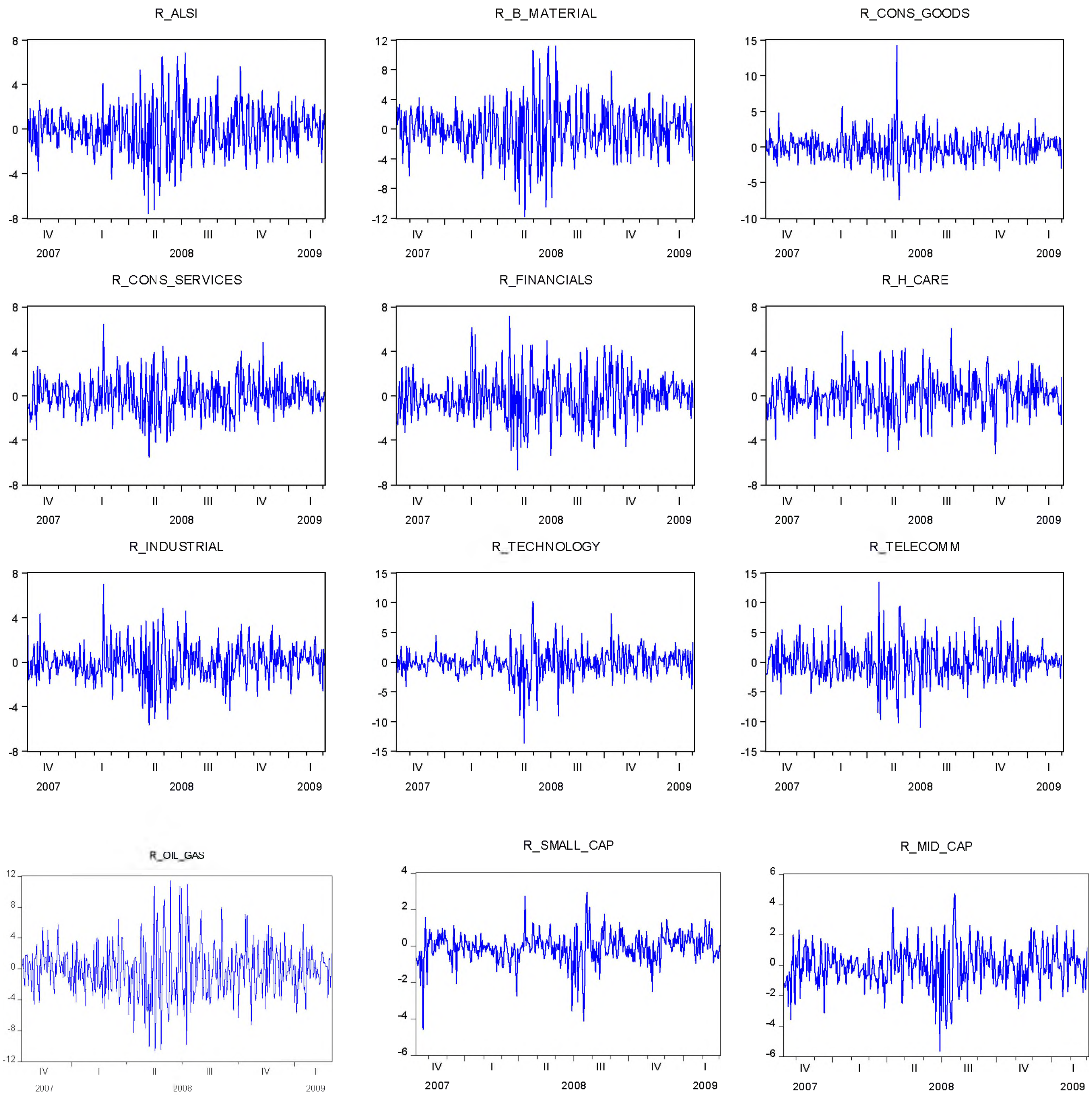




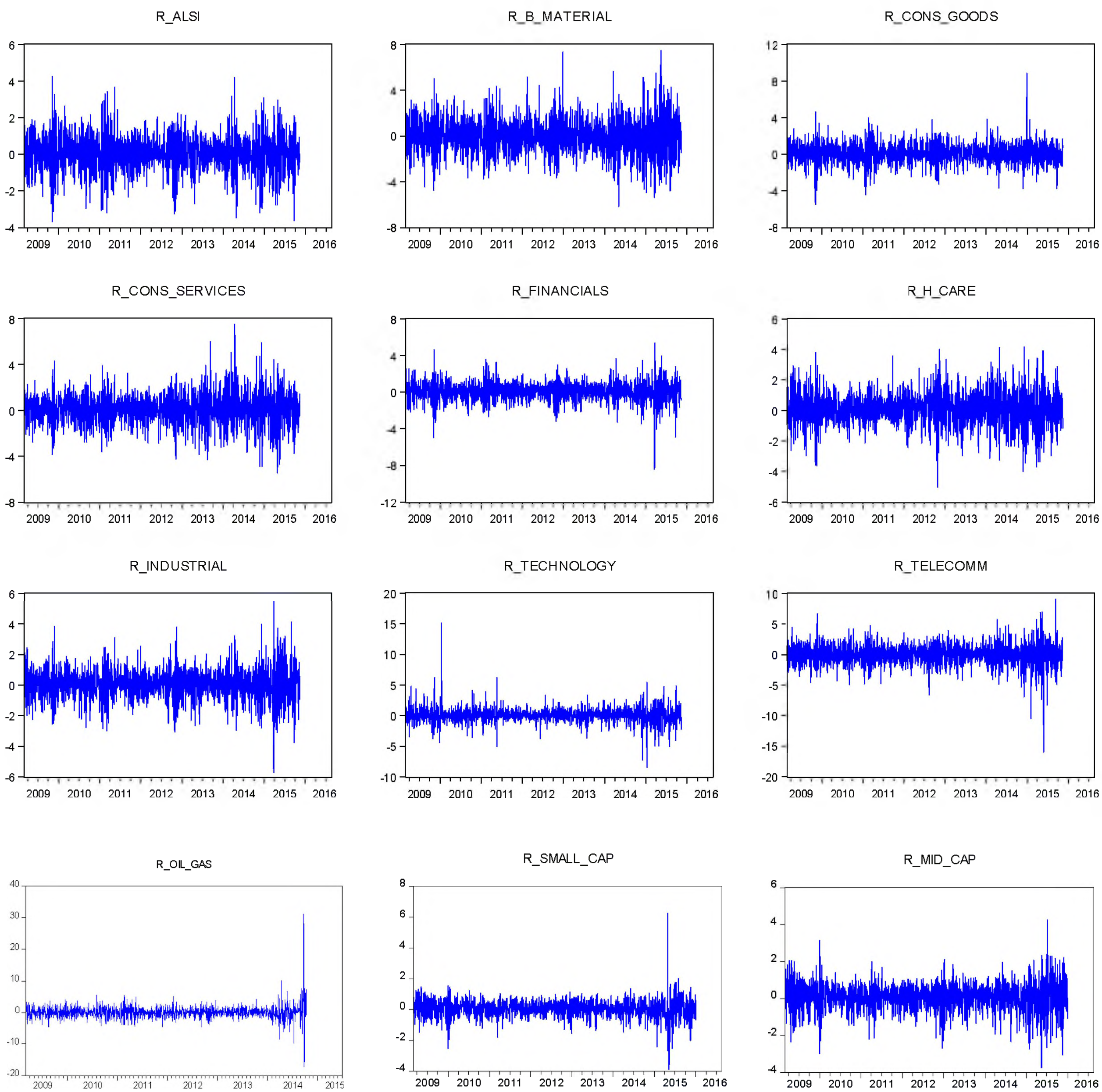
Pre Crisis Period



During Crisis Period

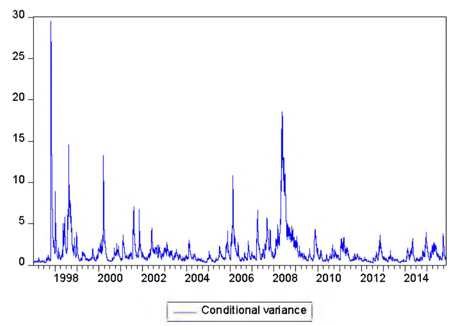


Post Crisis Period

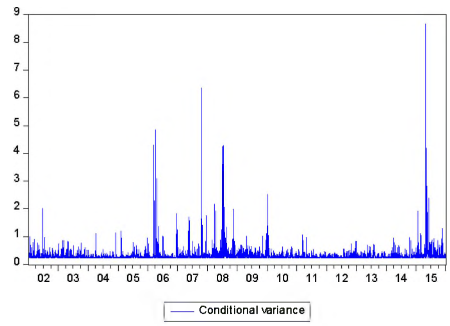


APPENDIX B3: Conditional variance for benchmark and sector indices- Whole sample period

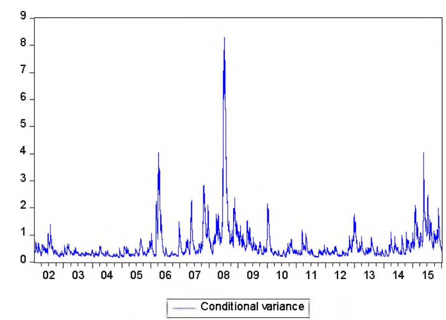
ALL SHARE



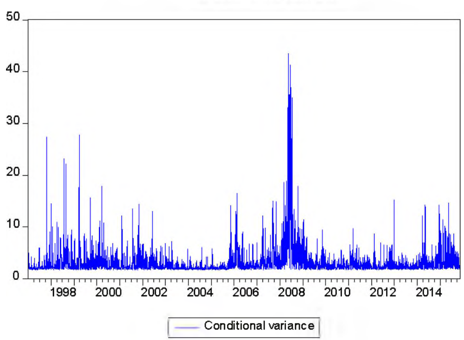
SMALL_CAP



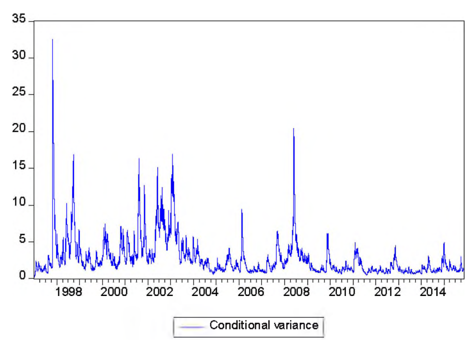
MID_CAP



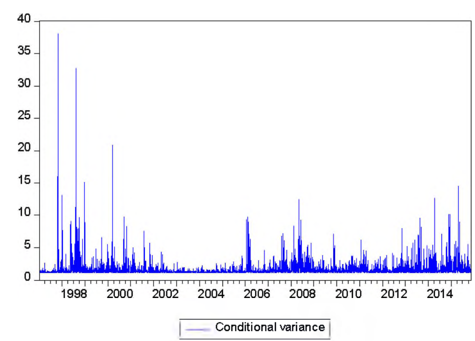
BASIC MATERIALS



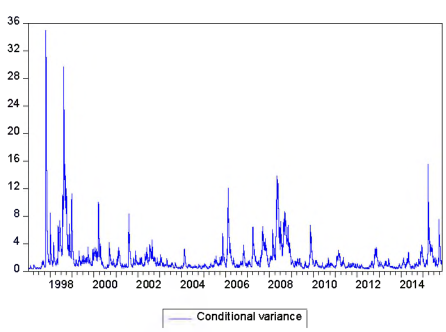
CONSUMER GOODS



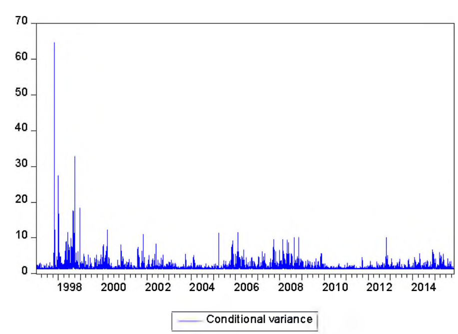
CONSUMER SERVICES



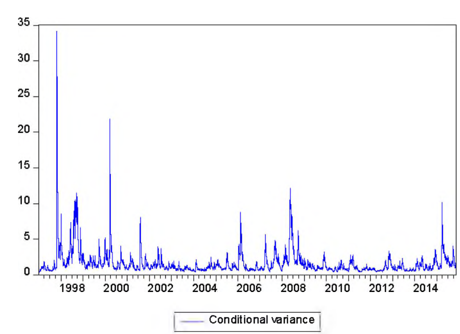
FINANCIALS



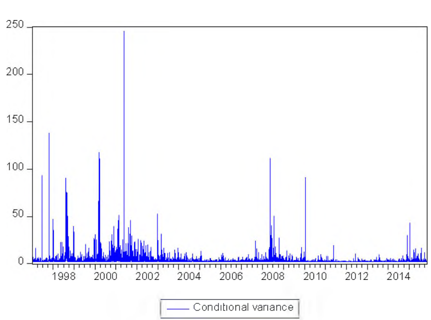
HEALTH CARE



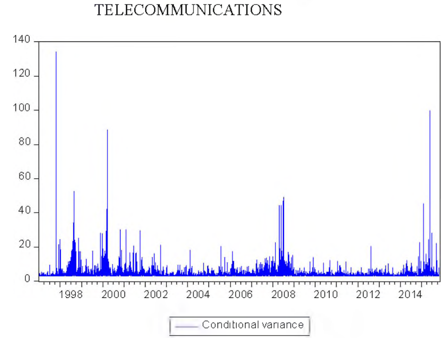
INDUSTRIAL



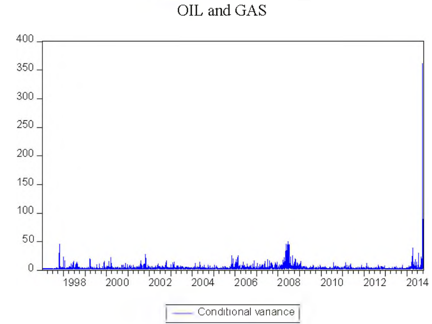
TECHNOLOGY



TELECOMMUNICATIONS

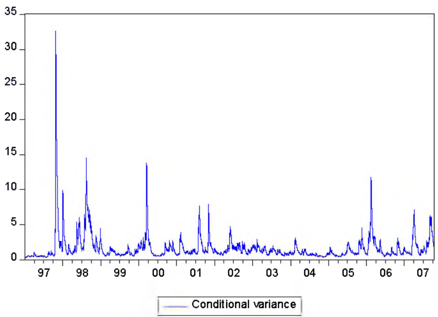


OIL and GAS

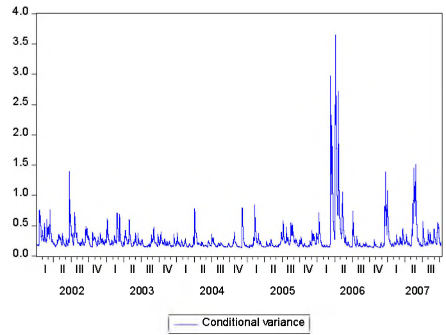


Pre-Crisis Period

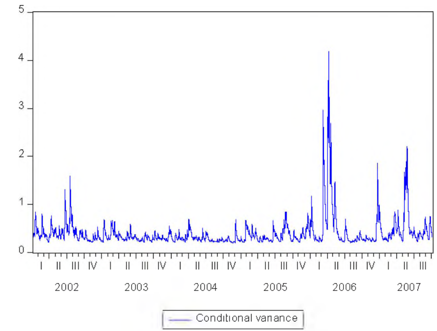
ALL SHARE



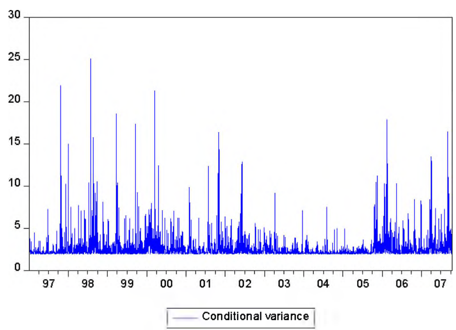
SMALL_CAP



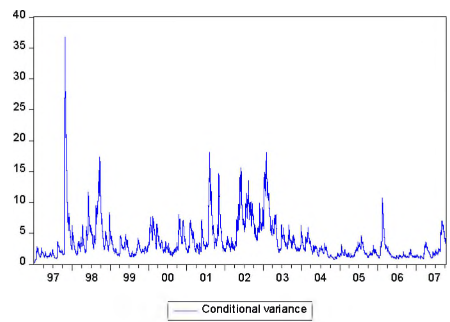
MID_CAP



BASIC MATERIALS



CONSUMER GOODS



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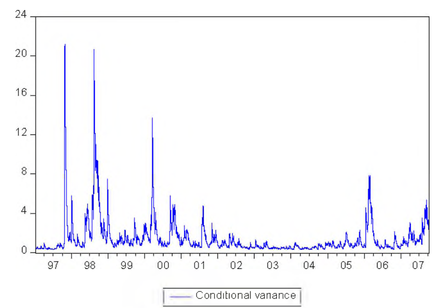
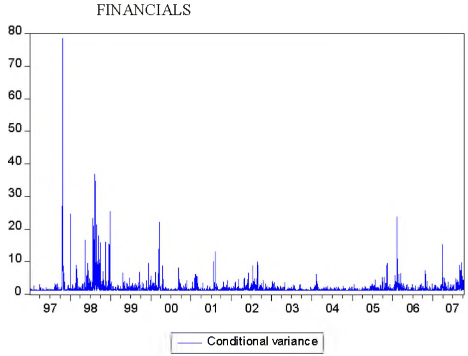
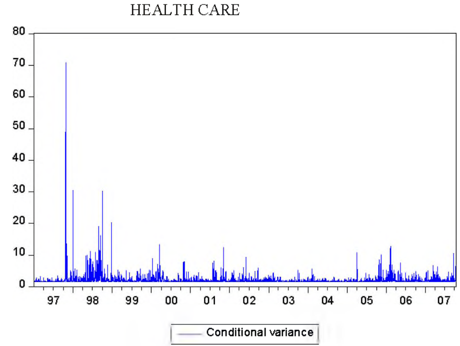


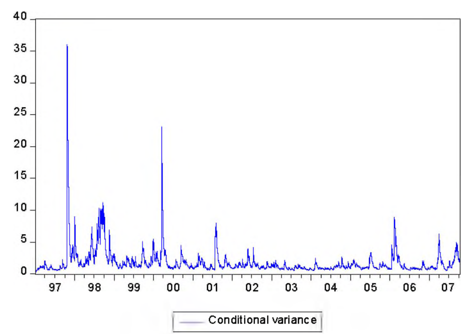
FINANCIALS



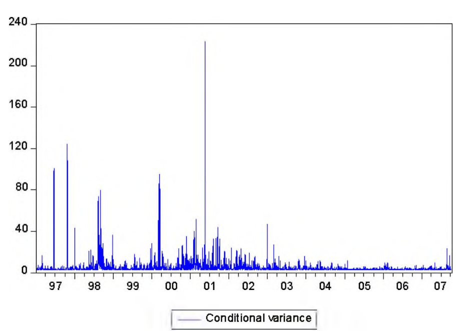
HEALTH CARE



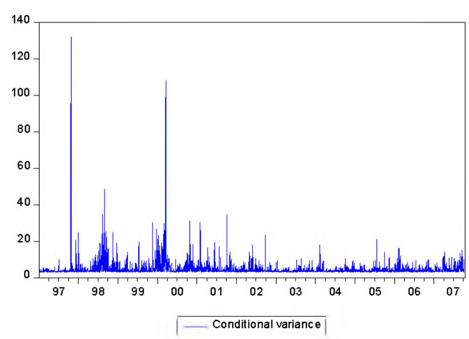
INDUSTRIALS



TECHNOLOGY



TELECOMMUNICATIONS



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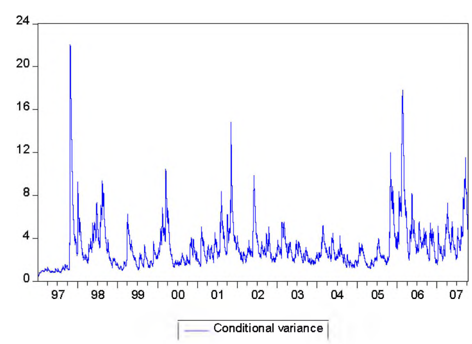
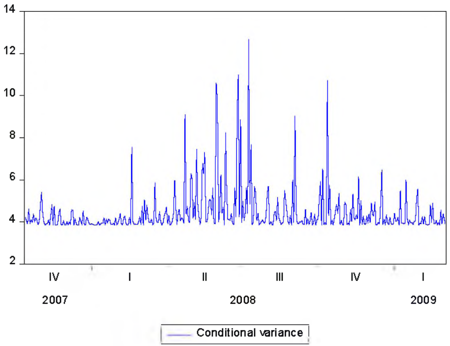
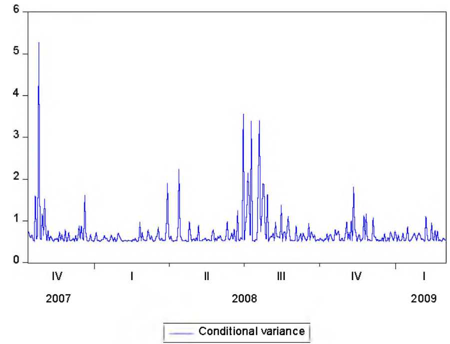


During Crisis Period

ALL SHARE



SMALL_CAP



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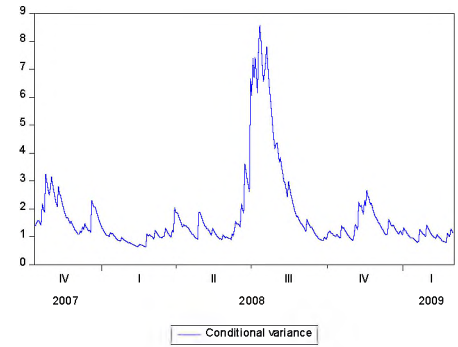
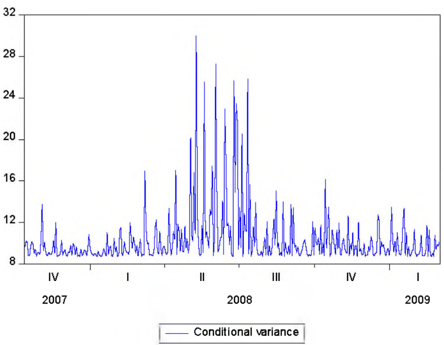
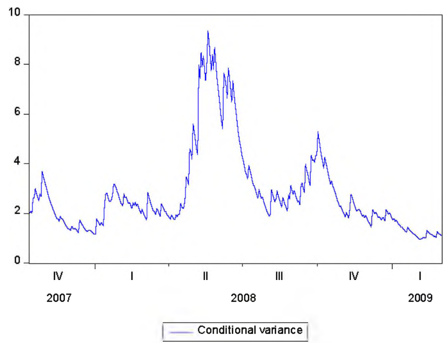


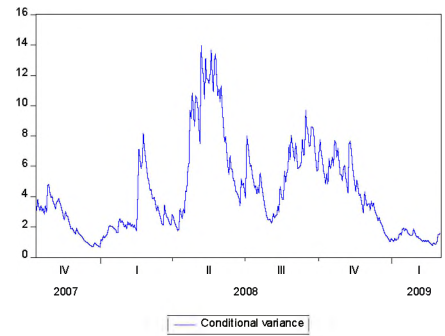
BASIC MATERIALS



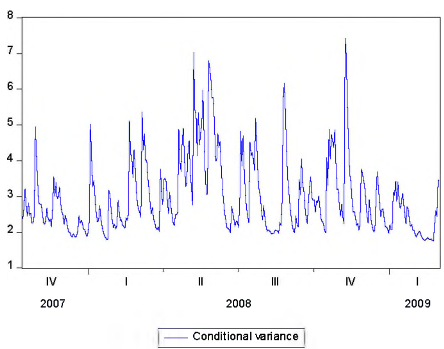
CONSUMER SERVICES



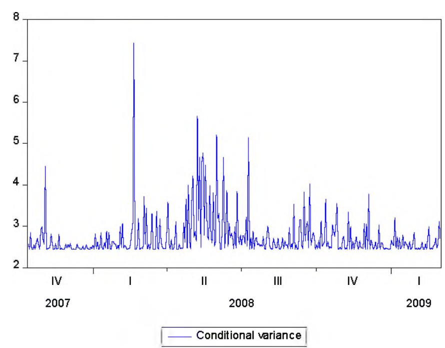
FINANCIALS



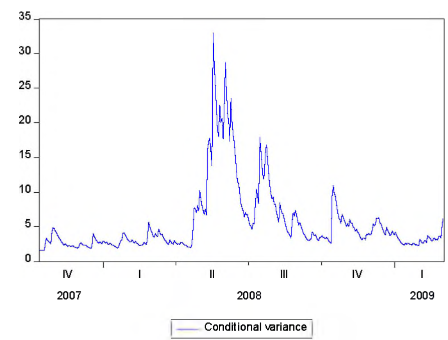
HEALTH CARE



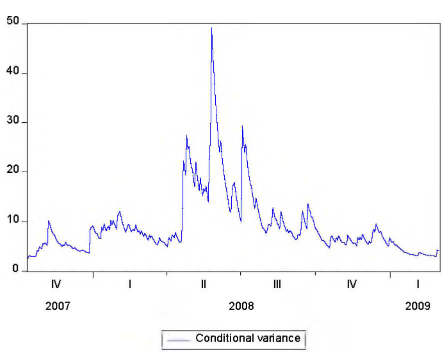
INDUSTRIALS



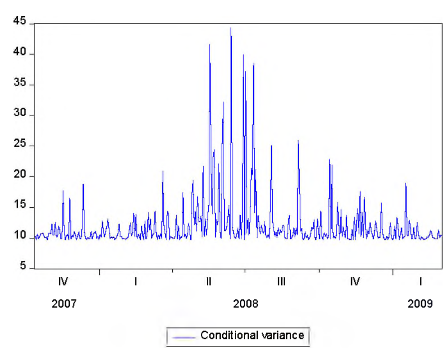
TECHNOLOGY



TELECOMMUNICATION

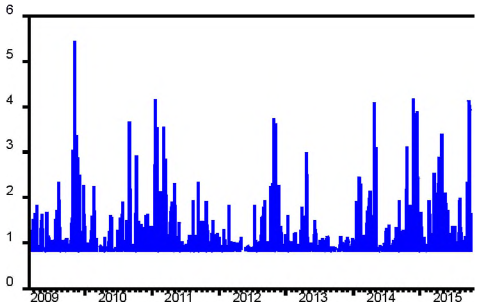


OIL and GAS



Post Crisis Period

ALL SHARE



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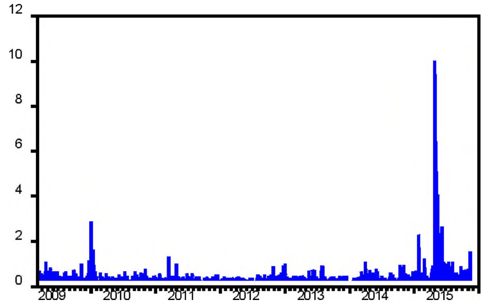

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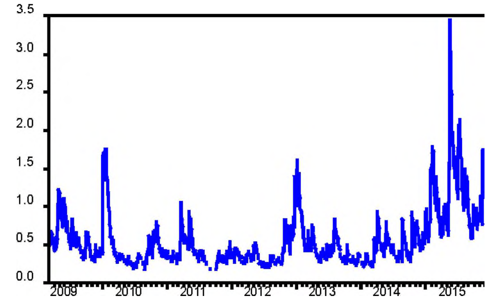
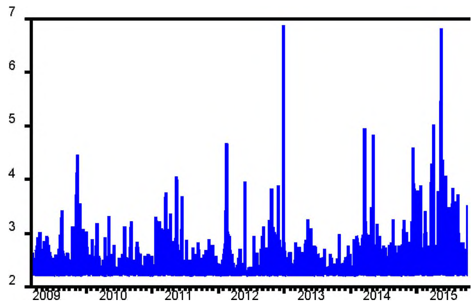
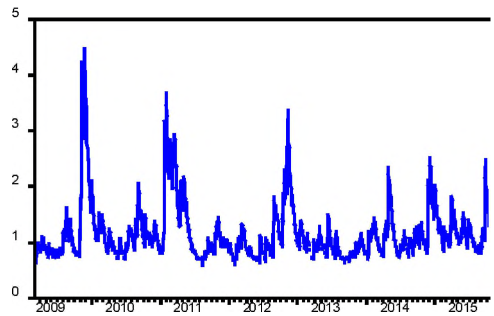


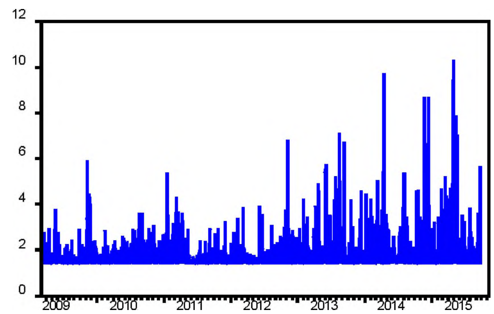
BASIC MATERIALS



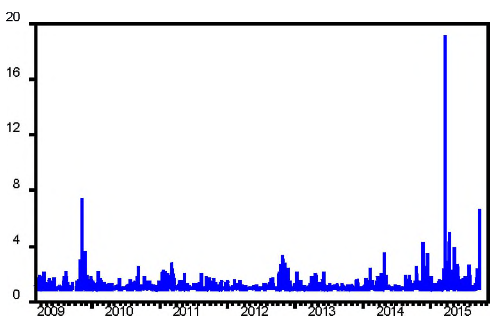
CONSUMER GOODS



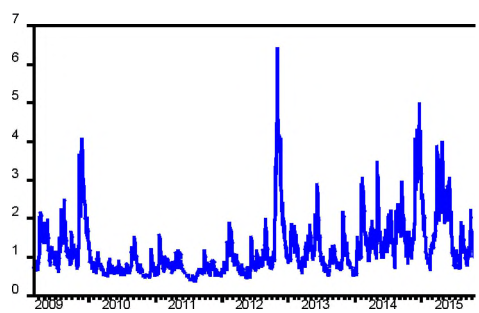
CONSUMER SERVICES



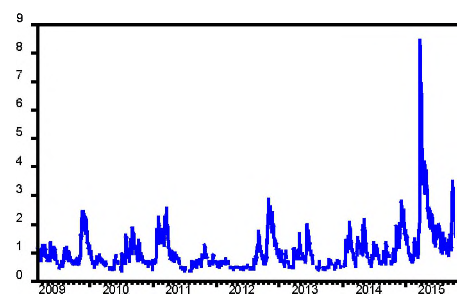
FINANCIALS



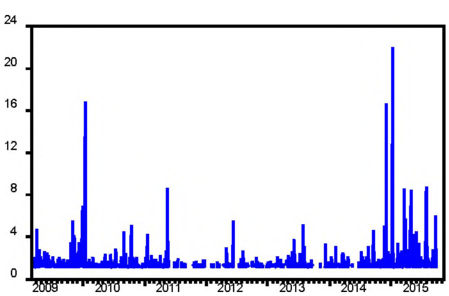
HEALTH CARE



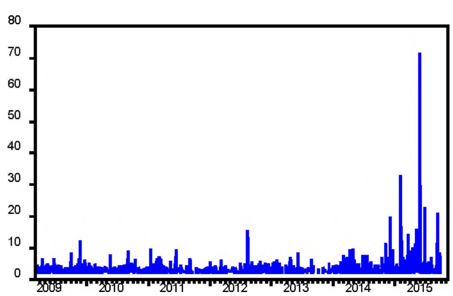
INDUSTRIALS



TECHNOLOGY



TELECOMMUNICATION



OIL and GAS