PERFORMANCE OF DEFENSIVE SHARES ON THE JSE DURING FINANCIAL CRISIS: EVIDENCE FROM ANALYSIS OF RETURNS AND VOLATILITY

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ABSTRACT

This study analyses whether historically defensive sectors on the JSE have – with respect to the market – proven to be defensive during the recent global financial crisis. By withstanding the shocks of market volatility, defensive industries (such as pharmaceuticals and consumer staples) are renowned for their consistent performance throughout the business cycle.

Using daily data for the period 2000–2009, the study compares the descriptive statistics of sector returns before and during the crisis. The volatility of each sector relative to the market index is calculated using the CAPM beta and a simplified volatility ratio. The same comparison is extended to the conditional volatilities of each of the sectors, which is estimated using the GARCH model and two of its extensions: the EGARCH and GJR GARCH models.

While no sector experienced a positive mean return during the financial crisis, Healthcare, Consumer Goods, Consumer Services and Industrials all proved less volatile than the market. Surprisingly, Telecommunications proved more volatile than the market and experienced leverage effects during the financial crisis. Since the timing of a recession is difficult to predict, defensive securities were found to be a useful investment tool for protection against adverse movements in the stock market.

DECLARATION

Except for those references acknowledged in the text, this thesis wholly represents my own work and no part has been submitted for a degree at any other university.

Signed: [signature]

Date: 10/04/2012

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CHAPTER 1: INTRODUCTION

1.1 Context of research

During times of financial crisis, investors seek shares that can provide stable returns, i.e. shares that withstand the shocks of market volatility. More specifically, investors desire shares with a history of stable earnings, good yields and slow, but dependable growth (Mahan, 1965:69). These non-cyclical shares are commonly referred to as defensive shares.

Bellehumeur (2008:1) argues that defensive stocks act defensively for one of two reasons. Either they are basic necessities that we cannot live without; or their prices are regulated by the government, protecting them against shocks in the business cycle. Goodspeed (2009:24) categorises defensive industries according to two phases of the business cycle: those that perform well at an upper turning point, that is, at the beginning of a downward phase; and those that perform well for the duration of a downward phase.

Industries in the first group include: aerospace and defence; utilities; tobacco; and basic industries (such as gold and timber). In this phase of the business cycle inflation rises as demand exceeds the supply of goods and services (Goodspeed, 2009:24). Rising input costs can cause liquidity problems and threaten operating stability. The rate of inflation has less of an impact on defensive industries, which produce goods with a stable demand, making them more appealing to investors. Industries that perform well during a downward phase include pharmaceuticals, food industries and insurance. This phase is characterised by rising interest rates and lower demand. Consumption thus decreases in all industries except those that are seen to be necessities (Goodspeed, 2009:22).

Limited empirical research has been done globally on the performance of defensive shares, and this applies to the recent financial crisis. Although there are a number of financial indicators that give warning of turning points in the business cycle, the exact timing of a recession is difficult to predict (Estrella and Mishkin, 1998: 55). As a result, the inclusion of defensive securities in a diversified portfolio for protection against adverse movements in the stock market is theoretically a useful investment tool. Their value in practice, however, warrants further investigation.

1.2 Goals of research

The primary goal is to determine whether the historically defensive industries have – with respect to the market – proven to be defensive during the recent financial crisis. Additionally, the industries will be ranked according to their performance and an attempt will be made to explain why they have acted in such a fashion.

1.3 Methods/ procedures/ techniques

A post-positivist research paradigm will be adopted to perform the analysis. The data will comprise of nine sectors on the JSE. Daily returns will be calculated from index prices between 03/01/2000 and 03/03/20009. The motivation behind choosing daily data is that the stock market reacts rapidly to new information. Lower frequency data, such as weekly or monthly data, do not capture the changes that occur within a day (Chinzara and Aziakpono, 2009:77). All price data will be obtained from Thomson Reuters Datastream 5.0.

The descriptive statistics of the index returns will be investigated to compare their performances relative to each other and the market. The FTSE/JSE All Share Index (ALSI) will be used as a proxy for the South African market as a whole. The sample period will be divided into two sub-periods; namely before and during the recent financial crisis. Industry mean returns and standard deviations for the two sub-periods will be compared. The same comparison will be extended firstly to the industries' beta coefficients. This will indicate each industry's level of risk relative to the market before and during the recent crisis. Secondly, the comparison will be extended to the industries' conditional volatilities, which will be estimated using the generalised autoregressive conditional heteroscedasticity (GARCH) model and two of its extensions, namely the GJR (Glosten, Jaganathan and Runkle) GARCH and the exponential GARCH (EGARCH) models.

The official turning points of the South African business cycle will be obtained from the South African Reserve Bank's (SARB) website. SARB identified only one downswing since 2000, beginning in December 2007 and ending in August 2009. The business cycle however lags behind that of the stock market (Goodspeed, 2009:21). To ensure an accurate benchmark is used for the financial crisis, the peak of the stock market cycle – indicated by the ALSI on 11/10/2007 – will represent the start of the downturn.

1.4 Organisation of study

The study is organised as follows: Chapter 2 discusses the theoretical literature relevant to the study. This includes a review of Business Cycle Theory, Modern Portfolio Theory (MPT), market efficiency and asset pricing models. Pertinent empirical literature is then reviewed, focusing on studies that analyse and compare the performances of different sectors. Chapter 3 sets out the analytical framework that will be followed. This includes the specification of the models, as well as a brief discussion about the data and *a priori*. Chapter 4 presents and discusses the results, comparing them with the literature and *a priori*. Chapter 5 concludes on the study's findings and provides potential areas for further research.

CHAPTER 2: THEORY AND LITERATURE REVIEW

2.1 Introduction

This chapter analyses the theoretical and empirical literature relating to the performance of defensive shares. Section 2.2 begins with a historical background to Business Cycle Theory and changes in South Africa's business cycle. This is followed by an analysis of industry performances in relation to different phases of the business cycle, including a classification of defensive and cyclical industries. The trade-off between risk and return is discussed in Section 2.3 under Modern Portfolio Theory (MPT), followed by a look at the importance of the Efficient Market Hypothesis (EMH) (Section 2.4) and its alleged effect on the business cycle. Section 2.5 discusses two popular models used in asset pricing, namely the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Section 2.6 summarises the findings of the limited empirical literature on defensive sectors and industry performance. Finally, Section 2.7 summarises the chapter.

2.2 The business cycle

2.2.1 Business cycle theory

The idea that economies move in cycles dates back to the work of Burns and Mitchell (1946). They suggested that cycles were caused by expansions in many economic activities occurring at a similar time (Burns and Mitchell, 1946:3). These expansions were followed by contractions and revivals until the next expansionary phase occurred in the recurring cycle. Each cycle is made up of four phases: an upturn (expansion), an upper turning point (peak), a downturn (contraction) and a lower turning point (trough).

Khomo and Aziakpono (2007:196) point out that while this cycle is commonly referred to as the business cycle today, a distinction should be made between a classical business cycle and a growth cycle. The classical business cycle was described above by Burns and Mitchell (1946), whereby expansions are followed by contractions in numerous economic activities. A growth cycle, on the other hand, is described as the fluctuation of the normal growth rate around the potential long-run growth rate. Following Khomo and Aziakpono (2007), the business cycle in this study will refer to both the classical and growth cycles, treating them as the same.

The upward and downward phases of South Africa's business cycle are displayed in Table 2.1. The South African economy is currently in the upward phase of the fifth business cycle since the early 1980's. Although South Africa's business cycle is closely correlated with the global business cycle, evidence of its resilience to external shocks is provided by the fact that it continued its upward trend during the global recession of 2001 (Khomo and Aziakpono, 2007:201).

There are several theories that attempt to explain the source of business cycles. Initially, business cycle analysts believed that each phase of the business cycle generated the phase that followed, resulting in an economy that is caught in a continuous, "self-sustaining cycle" (Chatterjee, 2000:1). A problem with this theory, according to Chatterjee (2000:1), is that an economy cannot achieve stable, sustainable economic growth, requiring the need for firm countercyclical policies.

The shock-based theory, according to Khomo and Aziakpono (2007:196), is based on the belief that there is always an achievable, full employment level of output. This full employment level of economic activity can be raised by an increase in the population or the discovery of new technologies. Without population growth or technological discoveries, this level will remain unchanged. Shocks to the economy temporarily move it away from its full employment level, resulting in a business cycle (Khomo and Aziakpono, 2007:196).

Monetary theorists are of the opinion that the business cycle is caused by changes in monetary policy, due to the observed effects of monetary aggregates on the real economy (Khomo and Aziakpono, 2007: 196). Macfarlane (1993:8) suggests that since loose monetary policy is linked to upswings in economic activity and tight monetary policy linked to downswings, one could argue that irregular changes in the money supply cause fluctuations in economic activity.

TABLE 2.1: PHASES OF THE SOUTH AFRICAN BUSINESS CYCLE

Business Cycle	Downward Phase	Length (months)	Upward Phase	Length (months)
1	Sept 81 – Mar 83	19	Apr 83 – Jun 84	15
2	Jul 84 – Mar 86	21	Apr 86 – Feb 89	35
3	Mar 89 – May 93	51	Jun 93 – Nov 96	42
4	Dec 96 – Aug 99	33	Sept 99 – Nov 07	99
5	Dec 07 – Aug 09	21	Sept 09 -	25+

Source: SARB website

Real Business Cycle Theory proposes that cyclical movements in the economy are caused by changes in productivity (Khomo and Aziakpono, 2007:196). Such changes in output are caused by improvements in technology and workers' skills, which affect the supply side of the economy. Chatterjee (2000:2) points out that in contrast to the other theories, real business cycle theorists believe that business cycles would still occur without monetary or fiscal disturbances.

The debate as to which theory is correct is beyond the scope of this study. Of interest, however, are three observations of business cycles that, according to Khomo and Aziakpono (2007:197), past studies share in common. Firstly, while business cycles follow a similar pattern, their length is unknown and cannot be accurately predicted. Fuhrer and Schuh (1998:6) suggest that because asset prices are based on investors '*ex ante*' expectations, changes in market expectations can have sudden, significant affects. As a result, no one has ever accurately predicted when an upturn will end (Fuhrer and Schuh, 1998:6).

Secondly, a steady rise in the stock market normally indicates a boost to the economy in the near future (Khomo and Aziakpono, 2007:197). In other words, the stock market cycle tends to lead the business cycle. Since the stock market can also be affected by the economy, this does not imply that the rise in the stock market causes the improvement in the economy. Goodspeed (2009:21) agrees that the stock market cycle leads the business cycle, arguing that the stock market is one of the best short-term indicators of business cycle turning points. While there have been bear markets (i.e. downturns in the stock market) in the United States that were not followed by economic recessions, the US economy has never experienced a recession that was not preceded by a bear market (Goodspeed, 2009:22).

According to Goodspeed (2009:22), there are three explanations for the stock market leading the business cycle. Firstly, investors don't invest based on current economic variables, but instead use forecasted variables. The reason for this is that most economic information that is presently available has already been built into share prices. The second explanation is that while investors react to the present economic environment, the financial indicators that they watch tend to lead business activity. Such indicators would include company profits, takeover bids, etc. The final explanation is that reversals in share prices, or changes in share price movements, are partially responsible for subsequent reversals in economic activity. This is because changes in share prices are known to affect business confidence and spending decisions (Goodspeed, 2009:22).

Khomo and Aziakpono's (2007:197) final point about business cycles is that upturns and downturns in the business cycle don't only affect a few industries or sectors, but the entire economy. Bodie, Kane and Marcus (2005:579) point out that the performances of different industries do however vary as the economy moves through different phases of the business cycle. The more sensitive an industry is to the business cycle, the greater its variation in earnings.

2.2.2 Industry analysis

Bodie *et al* (2005:588) argue that three factors can determine an industry's sensitivity to the business cycle. The first factor is the sensitivity of an industry's sales to business conditions. Industries with a low sensitivity to the state of the economy include basic necessities, such as food, drugs and medical services. Included in this category is the tobacco industry, for which income levels do not have a major effect on demand. Industries that are highly sensitive to business conditions include steel, machinery, automobiles and transportation.

The second factor that affects business cycle sensitivity is operating leverage (Bodie *et al*, 2005:588). Operating leverage refers to the ratio of fixed to variable expenses. Since variable costs are directly proportionate to the level of production, firms with a higher percentage of variable costs will be less sensitive to business conditions. This is because such firms can readily reduce costs as sales fall during an economic downturn. Firms with a high proportion of fixed costs, on the other hand, cannot easily adjust costs to offset a fall in sales. Such firms are said to have high levels of operating leverage, since changes in business conditions have a greater impact on profitability (Bodie *et al*, 2005:588).

The third factor that affects an industry's sensitivity to business conditions is financial leverage. Financial leverage describes the manner in which a firm finances its activities, or more specifically, the allocation between debt and equity. Financial leverage increases with a rise in debt. According to Bodie *et al* (2005:590), finance costs on debt are payable regardless of sales levels. The higher the level of financial leverage, the greater the interest charges and the more sensitive a firm is to the state of the economy.

While a high financial leverage, operating leverage and sensitivity of sales do increase an industry's investment risk, Bodie *et al* (2005:590) argue that investors should not necessarily choose industries with low sensitivities to business conditions. While such industries perform well during downturns, they are outperformed by riskier industries during upturns. Goodspeed (2009:22) identifies which industries perform the best at different stages of the business cycle. Towards the end of a recession, industries that are sensitive to a change in business conditions are outperformed by the market. Credit-sensitive shares (e.g. financial shares) rise with a recovery in the economy and the accompanied increase in loan demand. Bodie *et al* (2005:591) suggest that low levels of inflation and interest rates, which characterise the end of a recession, also favour financial firms.

At the start of an upturn, the reviving economy is characterised by increases in consumer confidence and personal income (Goodspeed, 2009:22). Consumer durables, which include consumer items such as computer equipment and white goods, thus become attractive investments. Media also performs well as a result of increased advertising expenditure. During an expansion, characterised by rapid economic growth, firms expand capacity to meet increasing consumer demand (Goodspeed, 2009:22). Capital goods industries, such as equipment, transportation and construction, thus become attractive investment opportunities. The rapid expanding of companies is accompanied by a boom in the property market. Bodie *et al* (2005:591) argue that banks are also attractive investments during an expansion. When the economy is growing, loan demand is high and defaults on loans are low, increasing bank profitability.

At the peak of the business cycle, inflation rises as the demand for goods and services exceeds supply (Goodspeed, 2009:24). Inflation has less of an impact on large companies with high levels of liquidity and operating stability. Basic industries involved in the extraction and processing of natural resources (such as minerals and timber) thus become attractive investments (Bodie *et al*, 2005:591). Inflation also should not have as much of an effect on industries that are subsidised by the government (e.g. utilities). Finally, the beginning of a recession is characterised by high interest rates and a decrease in demand (Goodspeed, 2009:24). Consumption expenditure falls in all industries except basic necessities. Consumer staples, such as pharmaceuticals, insurance, telecommunications and food industries, thus tend to outperform other industries. In contrast, financial firms are adversely affected by falling loan demand and rising default rates (Bodie *et al*, 2005:591).

2.2.3 Cyclical and defensive industries

Industries that experience above-average sensitivity to business conditions are commonly referred to as cyclical (Bodie *et al*, 2005:579). According to Johnson and Polk (2002:2), the earnings of cyclical firms fluctuate sharply with the state of the economy. Profits (or asset returns) thus exceed the market average during expansions, but fall below the market during recessions (Goodspeed, 2009:23). Lamfalussy (1961, in Maes, 2009:7) argues that cyclical, or 'enterprise' investments are made during rising markets when profits are growing and there is little market uncertainty. Such investments are a response to expansion policies, which lead to technological innovation and capacity increases.

Producers of durable goods, such as automobiles and household goods, are typical examples of cyclical industries (Goodspeed, 2009:23). Bodie *et al* (2005:580) argue that such goods are sensitive to business conditions because their purchase can be deferred during a recession. Producers of capital goods, such as equipment and machinery, are other examples of cyclical industries. Bodie *et al* (2005:581) define capital goods as those used by other firms in the course of their own production. When demand is high, companies that are expanding are required to purchase capital goods. In contrast, when demand is low, there is little need for expansion or the purchase of capital goods. The capital goods industry therefore performs well during an expansion but poorly during a recession (Bodie *et al,* 2005:581). Finally, banks, media and general retailers are all renowned cyclical industries (Goodspeed, 2009:23).

Non-cyclical, 'defensive' industries produce goods and services for which sales and profits are relatively insensitive to the business cycle (Bodie *et al,* 2005:581). Unlike cyclical investments, these industries experience stable demand and are thus a relatively safe investment during declining markets (Johnson and Polk, 2002:2).While defensive share prices do not rise as much as the market-average during upturns, they fall by less than the market-average during downturns (Goodspeed, 2009:23). Johnson and Polk (2002:2) argue that when included in a diversified portfolio, they are thus a useful investment tool to hedge against sudden losses in other shares.

Lamfalussy (1961, in Maes, 2009:7) argues that defensive investments are made for protection against declining markets, when returns are falling and minimising losses becomes crucial. While these investments are made to protect against losses, they can increase capacity and boost profits. Defensive industries, such as food producers and retailers, pharmaceutical firms and public utilities, will outperform other industries when an economy enters a recession (Bodie *et al,* 2005:581). In contrast to other industries in the financial sector, insurance firms experience stable demand throughout the business cycle and can thus also be classified as a defensive industry (Goodspeed, 2009:24).

Another group of industries that is renowned for its defensive performance is 'vice' goods (Waxler, 2004:1). Also known as 'sin stocks', this group of industries includes anything that is not considered politically correct: for example, alcohol, tobacco, gambling and defense/weapons. According to Waxler (2004:2), the demand for these industries not only remains stable, but increases during volatile periods. One explanation for such a trend is that an economic recession leads to increased stress levels, leading to greater indulgence in activities such as alcohol consumption (Brenner and Mooney, 1983:1126).

A second explanation, proposed by Waxler (2004:14), is that vice goods appeal to an individual's 'inner contrarian'. In other words, people are tired of being pressurised into doing the right thing. An example of such pressure is the increasing publicity and support for socially responsible investing (SRI). In addition to vice stocks, such investments exclude any companies that use sweatshop labour, animal testing or profit from war (Waxler, 2004:14). Instead of succumbing to this public pressure, investors rebel against it by investing in vice shares.

2.3 Modern Portfolio Theory

Modern Portfolio Theory (MPT) is based on Markowitz's (1959, in Swisher and Kasten, 2005:75) proposition that investors require compensation for taking on additional risk. Such compensation would be in the form of increased returns. Where greater returns are not possible, investors require the minimum level of risk attached to a given investment. Bodie *et al* (2005:156) share the view that investment decisions are subject to a trade-off between risk and return, stating that it has been proven over time that less-risky assets provide lower average returns.

Howells and Bain (2008:186) define risk as "the probability that the actual return may differ from the expected return." Risk includes both upside risk, whereby the actual return exceeds the expected return, and downside risk, whereby the actual return falls below that which is expected. This definition of risk, which Howells and Bain (2008:186) refer to as 'actual risk', thus assumes that risk is symmetrical. Individuals' attitudes to risk may however be asymmetrical. A risk-averse investor may be more concerned about the possibility of a loss than that of a gain.

Markowitz further proposed that risk can be reduced through diversification. By investing in a variety of assets, diversification limits an investor's exposure to the risk of any individual asset. Bodie *et al* (2005: 174) in fact argue that "by placing one's eggs in many baskets, overall portfolio risk actually may be less than the risk of any component security considered in isolation." If two assets in a portfolio are negatively correlated, their individual returns offset each other to reduce the overall risk of the portfolio (Bodie et *al*, 2005:173).

A diversified portfolio is expected to be both profitable and unlikely to diverge from expectations. When constructing a portfolio, Bowen (1984:17) suggests that the purchase of an asset should be evaluated with reference to the portfolio. An asset should only be added to a portfolio if its purchase increases the overall level of satisfaction that an individual receives from that portfolio. This can be achieved in three ways: from an increase in overall return; from a reduction in exposure to risk; or from a satisfactory trade-off between risk and return (Bowen, 1984:17). Such a trade-off would depend on an investor's tolerance or appetite for risk.

It is important to note that diversification cannot reduce all types of risk. Howells and Bain, 2008:191) suggest that a fully diversified portfolio only eliminates specific, unsystematic risk which stems from events unique to securities or industries. Such a portfolio is only subject to systematic, market risk stemming from economy-wide events. Market risk is inherent in any security and thus cannot be reduced through diversification (Howells and Bain, 2008: 191).
Rosenberg (1991:21) points out that the more diversified a portfolio is, the lower the level of unsystematic risk. Neu-Ner and Firer (1997:57) argue that while a portfolio of thirty shares can reduce market risk by almost ninety percent, combining even a few shares in a portfolio can achieve considerable diversification benefits.

According to Bowen (1984:19), Markowitz's theory is based on analysing the risk and return of portfolios on an *ex-ante* basis. In other words, it derives from the expectations about the future as opposed to looking at past data in a retrospective, ex-post manner. Markowitz relied on several assumptions in building his theory. Firstly, all capital markets are efficient. In an efficient market, security prices reflect all information available in the market (Ball, 2009:8). The implications of market efficiency will be discussed in the next section.

The second assumption made by Markowitz (1959, in Bowen, 1984:19) is that individuals are both risk averse and rational decision makers. An investor that is averse to risk will choose an asset with the least risk attached to it for a given level of return. A rational investor maximises expected utility. Thirdly, Markowitz believed that this utility is based exclusively on mean returns and the standard deviations of such returns. According to Bowen (1984:17), Markowitz opted for standard deviation due to its ease of calculation. While its statistical properties make it a good proxy for risk, there are certain elements of risk that it ignores. If risk is defined as "a known probability distribution of possible outcomes" (Bowen, 1984:19), then variance fails to explain the chance of loss or complete insolvency. This limitation in Markowitz' theory could theoretically lead to poor investment decisions.

Finally, with the use of indifference curves, investors can rank individual portfolios based on their risk and return (Bowen, 1984:19). According to Rosenberg (1991:23), an indifference curves represents a trade-off that an investor is willing to make between risk and return. In other words, these curves connect all portfolios with the same level of utility. They are upward sloping as a result of the positive relationship between expected risk and return. The position of a portfolio on an indifference curve depends on the nature of the assets making up the portfolio. An increase in the riskiness of a portfolio's constituent assets would be represented by a movement up an indifference curve, whereas a move to less risky assets would be indicated by a move down the curve. A major benefit of diversification is that portfolio risk can be reduced without moving down an indifference curve. Howells and Bain (2008:188) argue that by combining assets in a portfolio, an investor can reduce risk without the sacrifice to return that would accompany a change to less risky assets.

A portfolio is efficient if it offers the highest return for a given level of risk, or the minimum risk for a given level of return (Swisher and Kasten, 2005:75). The Efficient Frontier, proposed by Markowitz (1959, in Swisher and Kasten, 2005:75), is a curve representing an infinite number of efficient portfolios. This curve is also upward sloping but flattens out at high levels of expected return, suggesting that there is a diminishing marginal rate of return. The allocation of each portfolio on the frontier is determined by three factors: its return, its standard deviation and its correlation coefficient.

The optimal portfolio for an investor is the efficient portfolio with the highest utility (Rosenberg, 1991:23). This point, which can be found where an investor's highest indifference curve intersects with the Efficient Frontier, depends on an investor's level of tolerance to risk. According to Rosenberg (1991:21), this can be determined by a number of factors, including: the investor's knowledge of investments; the investor's emotional reactions to an adverse outcome;

the financial position of the investor and reliance on the portfolio; and the time scale over which the investor expects to make a certain return.

2.4 The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) states that efficient, competitive markets "ruthlessly exploit all available information when setting security prices" (Ball, 2009:8). Fama (1965:90) defines an efficient market as one in which actual security prices represent precise estimates of their intrinsic values at all times. In other words, in an efficient market, asset prices must fully reflect all information available in the market.

Fama (1970, 383) identifies three forms of market efficiency: weak, semi-strong and strong. The weak form of efficiency implies that security prices reflect all information that can be derived from past trading data. According to Bodie *et al* (2005:373), this is because all historical data on security prices is freely available to the public. This form stems from the Random Walk Hypothesis (RWH), which states that current changes in share prices cannot be explained by previous price changes (Seneque, 1979: 18). Fama (1970, 387) argues that the RWH does not state that historical information on share prices is of no value in predicting future returns. It merely says that the chronological order of past returns has no effect on the distribution of future returns. The effect of random walk is that analysing historical data for trends will not improve portfolio performance (Seneque, 1979: 18). All that is required to reject the Random Walk Model is statistical evidence of non-random behaviour (Strebel, 1976: 15).

The semi-strong form of efficiency occurs if share prices reflect, and adjust, to all publicly available information in the market (Seneque, 1979: 18). In addition to price data, public information includes any particulars regarding company management, balance sheet composition, sales figures or future earnings (Bodie *et al*, 2005:373). Since all public information is freely available to market participants, investors cannot make excess returns from trading with such information. Investors can only make excess returns on inside information such as trade secrets. In contrast, the strong form of efficiency requires share prices to reflect both public and private information, making it impossible for investors to make excess returns on inside information (Seneque, 1979: 18).

Grossman and Stiglitz (1980:406) argue that a perfectly efficient market cannot exist. Investors require a return for gathering information, which is impossible if all available information is already included in share prices. Without an incentive to gather information, there would be no reason to trade and the market would collapse. According to Grossman and Stiglitz (1980:407), the level of inefficiency in a market will determine the time and money spent in gathering and trading on information. A sustainable market equilibrium thus requires sufficient arbitrage opportunities to reward investors for finding and acting on new information.

The EMH builds on from MPT in that for the EMH to hold, certain market conditions should be present. Firstly, there should be no transaction costs or taxes on the trading of shares (Fama, 1970:387). Secondly, any new information should be costless and immediately available to all market participants. Thirdly, investors should have homogenous expectations about the effect of current information on future share prices.

Fama (1970:387) argues that even if these assumptions do not hold in practice, efficiency can still be obtained in a market Transaction costs do not prevent share prices from reflecting all available information. As long as a sufficient number of market participants have immediate access to new information, the market can still be considered efficient. Finally, investors are bound to disagree on the implications of certain information on future prices. A market will only be deemed inefficient if investors can consistently predict the effect of new information better than that included in share prices (Fama, 1970:388). Stated differently, Strebel (1976:15) argues that market inefficiency will only occur if "statistical non-randomness can be utilised to beat the market."

The EMH has a number of practical limitations. According to Ball (2009:12), its most obvious limitation is that it focuses exclusively on monetary exchange and the demand side of the market. The EMH simply states that investors will trade on new information until a new equilibrium is obtained and no additional gains can be made from trading. It says nothing about supply side factors such as how much information is available, how reliable it is or where it came from. While real factors such as these are no doubt important, Ball (2009:13) argues that finance literature has made its greatest breakthroughs by ignoring them.

A second limitation of the EMH is that it treats information as an objective commodity. The reality is that investors have varying beliefs and thus interpret new information differently (Ball, 2009:13). Furthermore, investors do not only act on their own beliefs, but also on their beliefs about the beliefs of others. Since complete, timely information is not available during periods of rapid price change, investors must instead speculate and base their decisions on incomplete information. Speculation about others' motives for trading is thus a major cause of rapid price changes.

The EMH has received a large amount of blame for the recent global financial crisis. According to Ball (2009:8), critics of the EMH argue that it is responsible for the underestimation of the dangers of asset bubbles. An asset bubble is an unusually large increase in security prices, followed by a sudden, unusually large collapse. As mentioned, the EMH states that market prices correctly reflect all available information in the market. Following this 'flawed' outlook, investors and regulators feel no need to verify the intrinsic values of the over-priced securities, and thus fail to detect the formation of asset bubbles before it is too late (Ball, 2009:8).

Ball (2009:8) argues that while the EMH is not without its limitations, it cannot be blamed for the financial crisis. Financial crises and, more specifically, asset bubbles in organised markets occurred long before the idea of efficient markets was first introduced. The first recorded asset bubble, known as 'tulip mania', occurred in the Netherlands in 1637. The EMH was only introduced by Eugene Fama in 1965, questioning claims that it is responsible for the formation of bubbles.

Furthermore, the argument that the EMH promotes price-taking – thus leading to the build up of asset bubbles - is inconsistent with what occurs in practice. This can be better understood by distinguishing between active and passive portfolio management. Active investment aims to identify and profit from under- or overvalued securities (Bodie *et al*, 2005:378). In contrast, passive investment involves a buy-and-hold strategy with a diversified portfolio, without trying to beat the market. Since securities are correctly priced under the EMH, there are theoretically no arbitrage opportunities to justify using an active investment strategy. Ball (2009:8) argues that the majority of investment funds are actively managed, despite overwhelming evidence that very few active managers are able to consistently outperform the market. The EMH thus cannot be blamed for an investment strategy that it does not advocate.

Weaknesses in the EMH in explaining market anomalies (such as asset bubbles) have led to increased support of behavioural finance. In contrast to the EMH, which assumes that investors are rational, behavioural finance acknowledges the effect of investor sentiment on the formation of stock prices (Chuang, Lo and Ouyung, 2010:14). In other words, behavioural finance theory uses psychological factors to explain errors in decision-making. Such factors include over-confidence, optimism and regret aversion, whereby investors are reluctant to realise losses.

In defence of the EMH, Ball (2009:15) argues that behavioural finance is simply made up of "a set of disjointed and inconsistent ideas, some of which are rationalisations of the anomalies of others." Unlike the more refutable EMH, behavioural finance cannot be tested. Ball (2009:15) thus argues that behavioural finance is not a theory but simply "a collection of ideas and results." It thus appears that while behavioural finance cannot replace the EMH, it can be used in conjunction with the EMH to explain pricing anomalies.

2.5 Asset pricing models

2.5.1 The capital asset pricing model

The capital asset pricing model (CAPM), developed by Sharpe (1964) and Lintner (1965), is based on the theory that not all risks should affect asset prices. The expected return on an asset does not depend on its stand-alone risk, as some of the risk inherent in an asset can be avoided through diversification (Sharpe, 1964:426). Perold (2004:3) in fact argues that risk that can be removed through a diversified portfolio is not risk at all. The market beta of an asset measures the sensitivity of the asset's return to systematic risk inherent in the market, which cannot be reduced through diversification.

The CAPM builds on Markowitz' (1959, in Fama and French, 2004:26) model of portfolio choice, which assumes that investors are risk averse and are only concerned about the mean and variance of their single-period investment return. The portfolios chosen by investors are thus mean-variance-efficient, in that they maximise expected return, given the variance of portfolio return, and minimise the variance, given the expected return. The Sharpe-Lintner model adds two assumptions to the Markowitz model: Investors agree on the joint distribution of asset returns, and investors can borrow and lend at a risk-free rate of interest (Fama and French, 2004:26).

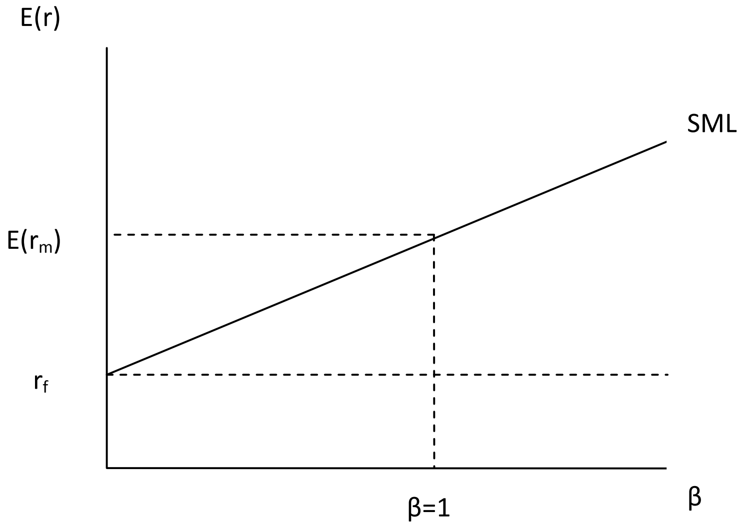
Perold (2004:16) summarises the assumptions of the Sharpe-Lintner CAPM as follows: Firstly, investors are risk averse and evaluate their diversified investment portfolios solely in terms of expected return and the standard deviation of the expected return, measured over the same single holding period. Secondly, capital markets are perfect in the following respects: assets are infinitely divisible; there are no transaction costs, taxes or short-selling restrictions; information is costless and available to everyone; and, as mentioned earlier, investors can borrow and lend at a risk-free rate of interest. Thirdly, investors have access to the same investment opportunities. Finally, the assumption that investors agree on the joint distribution of asset returns implies that they all make the same estimates of individual asset returns, standard deviations of return and the correlations among asset returns (Perold, 2004:16).

The Sharpe-Lintner CAPM expresses the expected return on asset $\boldsymbol{i}$ as the risk-free rate ($\boldsymbol{R_f}$) plus a risk premium, which is the asset's market beta (β) multiplied by the excess return of the market rate ($\boldsymbol{R_m}$) over the risk-free rate, thus($\boldsymbol{R_m} - \boldsymbol{r_f}$). Tofallis (2008:1358) specifies this relationship as:

$$R_i - r_f = \alpha + \beta(R_m - r_f) \qquad [2.1]$$

Where α is the intercept and β the slope of a linear relationship between the return on asset $\boldsymbol{i}$ and that on the market portfolio. In other words, β measures the sensitivity of an investment's rate of return to variation in the market rate of return (Tofallis, 2008:1358).

FIGURE 2.1: SECURITY MARKET LINE



Source: Bodie *et al* (2005:290)

The CAPM relationship between expected return and the market beta can be expressed diagrammatically by the securities market line (SML), shown in Figure 2.1. The market beta of asset *i* is equal to the slope of this line. Sharpe (1964: 426) points out that in an equilibrium market capital asset prices adjust so that a rational, diversified investor can attain any point along the SML. He may therefore only obtain higher returns – and move up the curve – by incurring additional risk. In a market which is in equilibrium, all assets must lie on the SML. If they are not, investors will be able to improve on the market portfolio and thus outperform the market (Perold, 2004:17).

According to Ross (1978:885), the positive orientation and intuitively pleasing predictions offered by the CAPM make it the central equilibrium model of financial economics. However, as a result its simplifying assumptions, the empirical record of the model is poor, limiting its use in application (Fama and French, 2004:25). This has led to numerous extensions of the Sharpe-Lintner CAPM, each of which tries to improve the consistency of the CAPM with actual behaviour.

One of the main criticisms of the Sharpe-Lintner CAPM is that the assumption of unrestricted risk-free borrowing and lending is unrealistic (Fama and French, 2004: 29). In response, Black (1972:450) developed a new version of the CAPM in which he relaxed the assumption of unrestricted borrowing and lending at a "risk-free" rate of interest. The main criticism of the Black (1972) version of the CAPM has to do with the short selling of risky assets. According to Fama and French (2004: 43), the assumption that short selling is unrestricted is as unrealistic as unrestricted risk-free borrowing and lending.

Merton (1973:868), on the other hand, criticises the single-period nature of the CAPM. In the Sharpe-Lintner CAPM, investors are only concerned about the wealth that their portfolios produce within the current period (Fama and French, 2004:37). In response, Merton (1973:868) developed the Intertemporal CAPM (ICAPM), in which he added the assumption that trading takes place continuously. In choosing a portfolio, the intertemporal maximiser thus considers the relationship between current period returns and returns available in the future (Merton, 1973:870). A drawback of the model is that the assumptions which it shares in common with the Sharpe-Lintner CAPM – especially that of homogenous expectations among investors – makes it susceptible to some of the same criticisms (Merton, 1973:868).

The assumption of perfect capital markets under the classical CAPM implies that assets are perfectly liquid or marketable. Mayers (1973:259) extended the classical CAPM under conditions of uncertainty to include both marketable and non-marketable assets. Examples of non-marketable assets include human capital, in the form of labour income, claims on government transfer payments and trust income. The main criticism of Mayer's model is its empirical testability. More specifically, critics have questioned whether there is a linear relationship between portfolio choices and investors' returns on non-marketable assets (Mayers, 1973:259).

2.5.2 Arbitrage pricing theory

Arbitrage pricing theory (APT), which was first introduced by Ross (1976), is an extension of the CAPM with weaker assumptions. van Rensburg (1997: 60) suggests that there are three major assumptions on which APT is based: markets experience perfect competition, free of asymmetric information amongst investors; investors are both averse to risk and insatiable with regard to their level of wealth; and investors agree that asset returns can be explained by a linear model with k number of factors. APT is based around the assertion that “only a few systematic factors affect the long-term average returns of financial assets” (Roll and Ross, 1984: 15). While not denying that there are many factors that have an influence on asset-price volatility, APT pays greater attention to those factors that have large-scale effects on entire portfolios.

Like the classical CAPM, APT is a single-period model, which states that there is a linear relationship between expected returns on assets and their sensitivities to other variables (Huberman, 2005:1). Unlike the CAPM, which only investigates sensitivities to the market return, APT measures sensitivities to numerous factors. These sensitivities are represented by a number of factor betas in APT, in contrast to the single market beta found in the CAPM. According to Huberman (2005:1), a linear relationship between assets’ expected returns and the factor betas will only exist if equilibrium prices offer no opportunities for arbitrage. This goes hand-in-hand with ATP’s assumption of perfectly competitive markets. Cetin (2004:1) defines a competitive market as one in which any security can be bought or sold without experiencing a change in price. Thus in a perfect market, assets are always correctly priced, preventing any potential opportunities for arbitrage.

Factors that have an affect on asset returns, but fail to explain major variations in market returns, are known as “idiosyncratic” factors (Roll and Ross, 1984: 15). Although they have an influence on firms and industries, they are not representative of general market conditions. Little emphasis is placed on these factors in APT, as their affect on asset returns is cancelled out through diversification. The majority of portfolio risk is explained by factors that are systematic to the general economy (Roll and Ross, 1984: 15). Actual returns are dependant on the same set of systematic factors. Portfolios do, however, have different levels of sensitivity to these factors, resulting in their varied performance. If a large, diversified portfolio - free of idiosyncratic risk - is protected from these systematic factors, it is in theory free of any risk (Roll and Ross, 1984: 15).

As the majority of portfolio risk stems from systematic factors, they are both the expected and actual determinants of portfolio returns (Roll and Ross, 1984: 16). Although Ross' (1984) original arbitrage pricing model is stated with an unlimited number of factors, Roll and Ross (1984:16) argue that they can be simplified to three or four, without reducing the adequacy of the model. This four-factor model can be expressed as:

$$E_j = r_f + (E_1 - r_f)(\beta_1) + (E_2 - r_f)(\beta_2) + (E_3 - r_f)(\beta_3) + (E_4 - r_f)(\beta_4) \qquad [2.2]$$

Where:

E_j = the total expected return on portfolio j.
r_f = the risk-free rate.
E_1 = the expected return on portfolio j attributed to changes in factor 1.
$E_1 - r_f$ =the market price of risk for factor 1.
β_1 = the sensitivity of portfolio j to factor 1.

According to Roll and Ross (1984:16), the four systematic factors that have the greatest effect on a diversified portfolio include: unexpected inflation; unexpected movements in risk premiums; variation in the level of anticipated industrial production; and unexpected changes in the term structure of interest rates. While there are a host of other factors that could be considered, Roll and Ross (1984: 16) argue that they would only significantly affect portfolio returns through the impact they have on the four chosen factors.

Huberman (2005:12) points out that the simplicity and flexibility of APT renders it useful for various practical applications, including: asset allocation, computing the cost of capital and evaluating fund performance. A drawback of such applications, according to Huberman (2005:14), is that many require extensions of the original model which violate APT's core theory: "assets are priced as if markets offer no arbitrage opportunities." The biggest weakness of APT, however, is that it does not specify what factors to include. As a result, different studies tend to include different sets of factors, leading to unique and contrasting findings (Huberman, 2005:13).

2.6 Empirical evidence

There is a wide body of empirical literature that compares company and sector performances in developed markets. To analyse the performance of various defensive shares during the recent financial crisis, Bellehumeur (2008) divided listed companies on the U.S. stock exchange into six categories: large pharmaceutical companies; utilities and pipelines; food companies; food and drug retailers; major fast food chains; and household goods. Only large, well established companies were selected from each sector as they are expected to be most resilient during a financial crisis (Bellehumeur, 2008:1). Performances were evaluated based solely on changes in share prices between 11 October 2007 and 6 August 2008. Other performance indicators, such as dividend payouts, were excluded from the investigation. This could be perceived as a weakness of the study.

Traditionally a defensive industry, pharmaceuticals surprisingly performed the worst of the six categories over the 10 month period (Bellehumeur, 2008:1). The four pharmaceutical companies chosen proved the least defensive, averaging a fall in price of 13.76 per cent. Food and drug retailers proved to be the second least defensive, averaging a fall in share price of 12.06 per cent. Bellehumeur's (2008:1) explanation for the poor performance of food and drug retailers is that, due to lower consumer demand, retail owners are unable to raise the prices of goods during a financial crisis, leading to lower profit margins and a subsequent fall in share prices. Fast foods, household goods and utilities all proved to be fairly defensive, with their share prices falling, on average, by 3.13, 3.55 and 3.74 per cent respectively. With three of the four fast food companies experiencing a rise in share price, Bellehumeur (2008:1) argues that fast food can be considered as a staple good. The most defensive category proved to be large food companies, which in fact rose in price by an average of 0.5 per cent.

Black, Buckland and Fraser (2002) compared the volatilities of UK sectors for the period 1968-2000. Using daily return data, standard deviations and CAPM betas were analysed for ten sectors, namely: Resources, Basic Industries, General Industries, Information Technology (IT), Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services, Non-Cyclical Services, Utilities and Financials. Based on mean annualised standard deviations, Black *et al*

(2002:35) found that IT proved the most volatile during the period. Cyclical Consumer Goods proved the second most volatile, followed surprisingly by Non-Cyclical Services. Despite their reputations for acting defensively, Utilities and Non-Cyclical Consumer Goods proved more volatile than Financials and Cyclical Services.

With the exception of Utilities and IT, Black *et al* (2002:35) found sector betas to all be close to one, suggesting their returns were highly correlated with the overall market. Utilities (0.695) experienced a beta of well below one, living up to its reputation as a defensive industry. Despite experiencing the highest standard deviation, IT (0.401) proved to be the most defensive sector during the period. According to Black *et al* (2002:35), this could be explained by IT having the lowest weighting in terms of market capitalisation, resulting in it being the least affected by movements in the overall market.

He and Kryzanowski (2007) compared sector returns and volatilities in Canada and the U.S. Monthly index values were analysed between January 1995 and December 2005 for ten sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health, Financials, IT, Telecom and Utilities. Financials proved to be the best performing sector, experiencing the highest mean return in both markets. The worst performing sectors were Materials in Canada and Telecom in the U.S. The U.S. sectors experienced a lower average standard deviation than their Canadian counterparts. According to He and Kryzanowski (2007:218), this is a result of the U.S. sectors being more diversified than those in Canada. In terms of standard deviation, IT proved to be the most volatile sector in both Canada and the U.S., whilst Consumer Staples proved the least volatile in both markets.

IT experienced the largest CAPM beta in both Canada (1.81) and the U.S. (1.56), suggesting it was most affected by shocks in the two markets. Utilities proved the least affected by market volatility, experiencing betas of just 0.26 in Canada and 0.42 in the U.S. Consumer staples (0.37), Telecom (0.76) and Health (0.86) all proved defensive in Canada, with betas of less than one. These sectors were surprisingly joined by Energy (0.64), Financials (0.80) and Consumer Discretionary (0.80), none of which are generally regarded as defensive industries (He and Kryzanowski, 2007:221). Similar results were reported in the U.S. market. Energy (0.60), again proving defensive, experienced the second smallest beta, followed by Consumer Staples (0.63) and Health (0.74). Telecom (1.02), which experienced a beta in excess of one, failed to live up to its reputation as a defensive industry.

There has been very limited research conducted on defensive industries in defensive markets, especially in South Africa. Neu-Ner and Firer (1997) analysed the performance of defensive shares on the JSE between 1993 and 1996, a period characterised largely by an upturn in the market. Based on the argument that shares with a beta close to one are not truly defensive, they compared the performances of those shares considered very defensive, possessing beta values of less than 0.5, to those not defensive, possessing beta values in excess of 1.1. Those shares with high beta values (characterised as being more sensitive to market fluctuations) experienced no change in average returns, at the cost of much higher anticipated risk. According to Neu-Ner and Firer (1997:56), such shares experience greater price volatility as a result of elevated levels of systematic risk, resulting in a less stable pattern of returns.

Those shares with low beta values (characterised as less sensitive to market fluctuations) experienced an increase in returns, accompanied by a fall in both expected risk and the level of dispersal in returns. According to Neu-Ner and Firer (1997:56), the greater returns realised on the low beta shares could largely be attributed to the performance of the economy. The high beta shares in fact experienced greater returns for the first eighteen months of the study. In line with finance theory, the low beta shares were less affected by the downturn in the market towards the end of the sample period, resulting in superior overall returns.

Using the generalised autoregressive conditional heteroskedasticity (GARCH) model, Malik and Hasan (2004) analysed the persistence of volatility in five major U.S. sectors between 1992 and 2003. The study examined weekly returns from five Dow Jones stock indexes: Consumer, Financial, Health, Industrial and Technology. The persistence of volatility was found to be high for all sectors, implying that shocks died away slowly. Shocks did, however, die off fractionally faster in the Health and Consumer sectors. Malik and Hasan (2004:211) found that accounting for volatility shifts caused by economic or political disturbances reduced the persistence of volatility, most notably in the Health and Industrial sectors.

2.7 Summary

The recurring cycle of economic activity is commonly referred to as the business cycle. The length of expansions and contractions making up this cycle cannot be forecasted with complete accuracy. Defensive industries, which are less sensitive to the business cycle than cyclical industries, outperform the market during an economic contraction. For this reason, they are potentially a useful investment tool to guard against an unanticipated downturn in the market.

Two asset pricing models that stem from modern portfolio theory and are widely used in finance literature are the CAPM and APT. Despite its limitations, the simplicity of the CAPM has led to it being extensively used in finance literature. While the flexibility of APT renders it useful for practical applications, it also leads to contrasting findings, making it a less attractive model than the CAPM for comparative purposes.

Both theory and empirical literature suggest that healthcare, utilities and consumer staples are defensive sectors. However, in contrast to finance theory, telecommunications failed to act defensively in several studies. The above review indicates that while a number of empirical studies analyse the descriptive statistics and CAPM betas of various sectors, there are few that focus on the South African market. Moreover, there appears to be no study that uses the GARCH model to analyse the conditional volatilities of South African sectors. The empirical analysis in the next chapter aims to fill these gaps.

CHAPTER THREE: METHODS AND DATA

3.1 Introduction

This chapter sets out the analytical framework to meet the objectives of the study. As discussed in Chapter 1, the primary issue is analysing the returns and volatilities of equity indices listed on the JSE. The descriptive statistics of these indices are firstly examined. Investors, however, are not only interested in the risk of a security on its own, but are also concerned about the risk of such a security (or index) relative to the market (Clark, 2007:33). A popular measure of this relationship is the CAPM beta, which is calculated and then compared to a simplified volatility ratio. Finally, analysing the conditional volatilities of the indices requires the estimation of univariate GARCH models.

The chapter is set out as follows: Section 3.2 identifies the tests used to ensure stationarity of data. Section 3.3 specifies and discusses the models used to analyse volatility. The CAPM beta and volatility ratio, as mentioned, are used to measure volatility relative to a market index. The conditional volatilities of the indices are estimated using the GARCH model and two of its extensions, namely the GJR GARCH and EGARCH models. Section 3.4 discusses the data used in the study, as well as issues with the data and *a priori* expectations. Section 3.5 provides a summary of this chapter.

3.2 Stationarity tests

A stationary process is one with a constant mean and variance over a period of time as well as a covariance that is not serially correlated (Gujarati, 2005:496). Chinzara and Aziakpono (2007:28) suggest that stationarity of time-series data is important for two reasons: it enables forecasting and it reduces the likelihood of regressions being spurious. A regression of two unrelated variables that are trending over time could result in a high R^2 (Brooks, 2008:319). In other words, a regression of non-stationary data can result in output that looks good, but is really of little value.

Following Chinzara and Aziakpono (2007:28), this study performs two tests for stationarity: the Augmented Dickey Fuller (ADF) test and the Kwiatkowski *et al.* (KPSS) (1992) test. The ADF test tests for a unit root which, if present, suggests that a series is non-stationary (Brooks, 2008:327). The null hypothesis in the ADF test states that the series contains a unit root. This null is rejected if the test statistic exceeds the ADF critical value, suggesting that the series is in fact stationary. As a result of the null hypothesis of a unit root, the test statistics follow a non-standard distribution. The ADF critical values, which are derived through simulation, are therefore larger in absolute terms than standard critical values. This implies that greater evidence is required to reject the null than under standard *t*-tests (Brooks, 2008:328).

The KPSS test tests directly for stationarity. The null hypothesis of a stationary series is rejected if the test statistic is smaller than the critical value. Brooks (2008:331) refers to the joint use of ADF and KPSS testing as "confirmatory data analysis", and the two tests should ideally come to the same conclusions for them to be robust. If the two tests provide different conclusions on a given series, it would be assumed that the series is non-stationary in level terms since the KPSS has greater power than the ADF.

3.3 Model specification

3.3.1 Capital asset pricing model (CAPM)

As discussed in Section 2.5.1, the Sharpe-Lintner CAPM expresses the expected return on asset ***i*** as the risk-free rate (R_f) plus a risk premium, which is the asset's market beta (β) multiplied by the excess return of the market rate (R_m) over the risk-free rate, thus ($R_m - r_f$). Tofallis (2008:1358) specifies this relationship as:

$$R_i - r_f = \alpha + \beta(R_m - r_f) \qquad [3.1]$$

Where α is the intercept and β the slope of a linear relationship between the return on asset ***i*** and that on the market portfolio. In other words, it measures the sensitivity of an investment's rate of return to variation in the market rate of return (Tofallis, 2008:1358).

An alternative approach, as followed by Tofallis (2008), is to exclude the risk-free rate in beta estimation. This approach is supported by Bodie ***et al.*** (2002, in Tofallis, 2008:1359) who state that most commercial providers of beta do not use the excess return form. This simplified relationship between an investment's return (R_i) and the market return (R_m) can be specified as follows:

$$R_i = \alpha + \beta R_m \quad [3.2]$$

Tofallis (2008:1359) points out that excluding the risk-free rate would result in a slightly deflated beta coefficient. These deflated betas are not expected to have a major effect on this study's findings for two reasons. Firstly, the focus is on whether a sector proves to be cyclical ($\beta>1$) or defensive ($\beta<1$) during a given period and not on the degree of its cyclical or defensive nature. Secondly, rankings based on sector betas are not expected to be distorted since all sectors will experience deflated beta coefficients. Following Samouilhan (2007) and Tofallis (2008), ordinary least squares (OLS) regression will be used to estimate the CAPM beta. This beta coefficient, from equation (3.2), is calculated as follows:

$$\beta = r\ \sigma_i/\sigma_m \quad [3.3]$$

Where σ_i and σ_m represent the standard deviations of the rates of return on investment ***i*** and the market, respectively, and ***r*** represents the correlation between the rates of return. From equation (3.3), it is clear that an asset (or index) that is perfectly correlated with the market would have a beta equal to one. An index that has a lower standard deviation than the market would have a beta of less than one, whereas an index with a standard deviation greater than the market would have a beta greater than one. Based on this principle, the study distinguishes between defensive industries ($\beta<1$) and non-defensive, cyclical industries ($\beta>1$). After estimating beta coefficients for each sector analysed in the study, sub-sector beta coefficients will be estimated for those sectors that prove to be defensive. This will indicate which sub-sectors are behind the defensive performance of their respective sectors. The industries will then be ranked according to their performances during the financial crisis. The lower the beta of an index during the crisis, the more defensive it will have proven to act.

One of many criticisms of the CAPM is that it assumes that the independent variable R_m (in equation 3.2) is free of error. Tofallis (2008:1359) argues that this problem, known as benchmark error, is inevitable when using an index as a proxy for the market. The 'market' in the CAPM theoretically refers to all global investments, including equities, bonds, commodities and derivatives. Since finding an ideal proxy for such a market is not possible, this study follows most empirical literature (Clark, 2007; Samouilhan, 2007; Tofallis, 2008) by using a suitable market index. More specifically, the FTSE/JSE All-share index (ALSI) is used as a proxy for the market portfolio. According to Tofallis (2008:1359), a consequence of using such an index as a proxy for the market is that the resulting beta coefficients are smaller than their true values. As this limitation is in line with other studies previously mentioned, it is not expected to have a significant effect on any of this study's outcomes.

A second criticism of the CAPM and its use in application is that it mixes together correlation and relative volatility. Tofallis (2008:1361) argues that a low beta could represent a high relative volatility that has been concealed by a low correlation. Investors might therefore mistakenly think that they have selected a defensive investment with a low volatility. Following Tofallis (2008:1361), this confounding of correlation and relative volatility is avoided by calculating a second form of beta:

$$\beta^* = \sigma_i / \sigma_m \qquad [3.4]$$

The new beta coefficient (β^*), known as the volatility ratio, excludes the correlation coefficient r. This approach was also used by Camp and Eubank (1985), based on the argument that β (in equation 3.3) fails to take diversifiable, unsystematic risk into account. On the other hand, β^* considers the total variation of an asset's return relative to the overall market variation (Tofallis, 2008:1361).

3.3.2 Conditional volatility

A fundamental problem with measuring volatility is that it is an unobservable or latent variable (Duncan and Liu, 2009:367). Typical measures, such as the realised variance or standard deviation of returns, can therefore at best be considered proxies for true volatility. This difficulty in measuring volatility is enhanced by the stylised features of financial data. Distributions of financial returns typically display fat tails, volatility clustering and signs of asymmetry (Duncan and Liu, 2009:367).

Excess volatility, volatility clustering and leverage effects are properties of financial data that can be captured by the autoregressive conditional heteroscedasticity (ARCH) and GARCH models proposed by Engle (1982) and Bollerslev (1986), respectively, and their extensions (Chinzara and Aziakpono, 2009:73). GARCH is a better and more popular model than ARCH because it is more parsimonious and avoids over-fitting (Brooks, 2008:393). The GARCH model is therefore less likely to breach non-negativity constraints.

GARCH models employ a maximum likelihood procedure, which essentially finds the most likely values for the model's parameters, given the actual data (Brooks, 2008:395). Signs of a change in volatility suggest that GARCH effects could be present in the residuals of the mean equation (Burger, 2008:339). Such effects appear when the variance of shocks to a variable is not constant, but varies over time. More specifically, ARCH effects are present if the conditional variance of current values of the error term depends on past values of the error term (Burger, 2008:340). These lagged values are known as the ARCH terms. The conditional variance of the error term can also depend on past conditional variance values, known as GARCH terms. Modelling a dependent variable on both GARCH and ARCH terms creates an autoregressive moving average (ARMA) variance model (Burger, 2008:340).

Conducting a GARCH analysis first requires the specification of an appropriate mean equation. The typical mean equation is specified as follows:

$$R_t = \mu + \varepsilon_t \qquad [3.5]$$

Where R_t represents the returns for each price index under investigation, μ is a constant and ε_t is a normally distributed error term with zero mean. In line with Burger (2008) and Chinzara and Aziakpono (2009), the mean equation will take the form of an ARMA (p, q) model. Using the Box-Jenkins procedure, the number of lags for the autoregressive (AR) and moving-average (MA) terms is selected based on the Akaike information criterion (AIC) and the Schwartz information criterion (SIC). Provided the ARMA specification displays no sign of autocorrelation, the number of lags with the lowest AIC and SIC is selected (Burger, 2008: 340). The models chosen for each dependent variable should be well behaved: free from serial correlation and with their characteristic roots falling inside the unit circle (i.e. have values of less than one).

Before estimating the volatility models, the mean equations must be tested for ARCH effects. As such, an ARCH LM test is performed, which is a Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity in the residuals of an estimated equation (Engle, 1982:999). While there are other methods to test for heteroscedasticity, such as White's (1980) heteroscedasticity test, the ARCH LM test is the most commonly utilised method within a GARCH framework and thus also used in this study. According to Chinzara and Aziakpono (2009:36), its procedure involves a regression of the squared residuals on a constant and lagged squared residuals up to lag q. If the test statistic (which follows a Chi-squared distribution) is significant, we can reject the null hypothesis and conclude that there is evidence of ARCH effects in the data and a GARCH model is then appropriate.

Chinzara and Aziakpono (2009:75) argue that a GARCH (1, 1) model sufficiently captures volatility clustering in financial data. Models of a higher order are thus seldom estimated in finance literature. Following Chinzara and Aziakpono (2009:75) and Malik (2011:546), the variance equation for the benchmark GARCH (1, 1) model is specified as follows:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad [3.6]$$

Where the conditional variance (h_t) is a function of the mean level of volatility (ω), news from the previous period (ε^2_{t-1}) and the lagged conditional variance from the previous period (h_{t-1}).

Brooks (2008:389) notes that h_t is a conditional variance and must therefore always be positive. Since the explanatory variables in equation (3.6) are all squares of lagged residuals, by definition the conditional variance cannot be negative. The conditional variance is known as such because it is a single period estimate of the variance based on all relevant past information (Brooks, 2008:392).

According to Duncan and Liu (2009:368), α and β (in equation 3.6) are measures of the 'ARCH effect' (the speed of the market's reaction to breaking news) and the 'GARCH effect' (the extent to which historical volatility influences current price changes), respectively. The sum of α and β measures the persistence of volatility for a given shock; for stationarity, $\alpha + \beta < 1$. Malik (2011:546) argues that most studies using high frequency data find this sum to be very close to one, suggesting that shocks are highly persistent. Duncan and Liu (2009:368) share this belief, stating that a value of close to one suggests that the volatility process has long memory.

While it accounts for volatility clustering, a limitation of the GARCH (1, 1) model is that it assumes that the impact of news is symmetric (Malik, 2011:546). In other words, it assumes that positive and negative shocks have the same effect on conditional volatility. Malik (2011:546) points out that there is extensive evidence, especially in broad market indices, that volatility in equity markets is asymmetric. Chinzara and Aziakpono (2007:37) argue that this asymmetry is a result of leverage effects whereby a lower share price causes an increase in a firm's debt-to-equity ratio, leaving shareholders less sure about future cash flows. Two extensions of the GARCH model that capture the asymmetric effects of news on conditional volatility are the EGARCH and GJR GARCH models.

Proposed by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993), the GJR GARCH model is simply a re-specification of the GARCH (1, 1) model. Its variance equation, which includes an additional term to account for asymmetry, is specified as:

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \qquad [3.7]$$

Where: $I_{t-1} = 1$ *if* $\varepsilon_{t-1} < 0$

= 0 otherwise

In the above specification, γ is the asymmetry coefficient, whilst I_{t-1} is the asymmetry component. Good news and bad news will therefore have impacts on the conditional variances of α_1 and $\alpha_1 + \gamma$, respectively. Chinzara and Aziakpono (2009:76) suggest that for the impact of news on conditional variance to be asymmetric, the asymmetry coefficient must be both significant and positive ($\gamma > 0$).

An advantage of the exponential GARCH (EGARCH) model is that it has a logarithmic functional form, which avoids the restrictive assumption of positive parameters included in the other GARCH models. For this reason, the EGARCH model is also utilised in this study. The conditional variance equation for the EGARCH model is:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \gamma \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \alpha \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}} - \sqrt{2/\pi}}\right) \qquad [3.8]$$

Volatility is asymmetric if $\alpha + \beta < 1$ and $\gamma < 0$. Alpha (α) is the coefficient of lagged residuals and beta (β) is the coefficient of the lagged conditional variance. If gamma (γ), the asymmetry coefficient, is significant and less than zero, a negative disturbance will lead to a higher conditional variance in the following period than a positive disturbance of the same scale (Chinzara and Aziakpono, 2007:8).

3.4 Data

3.4.1 Sources and properties of data

Daily returns are calculated from FTSE/JSE index prices between 03/01/2000 and 03/03/2009, totaling 2291 daily observations. In addition, the sample period is split into two sub-periods: before and during the financial crisis (as indicated by the stock market cycle), totaling 1943 and 348 observations respectively. Using these two sub-periods allows for a comparison of average returns and volatility for two phases of the stock market cycle, namely an upturn and a downturn. This will provide an indication of the effect of the financial crisis on a variety of equity indices. The data comprises of nine sectors on the JSE, their respective sub-sectors and the FTSE/JSE

All-share index (ALSI), which is analysed for comparative purposes. These nine sectors include: Oil and Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Financials, and Technology.

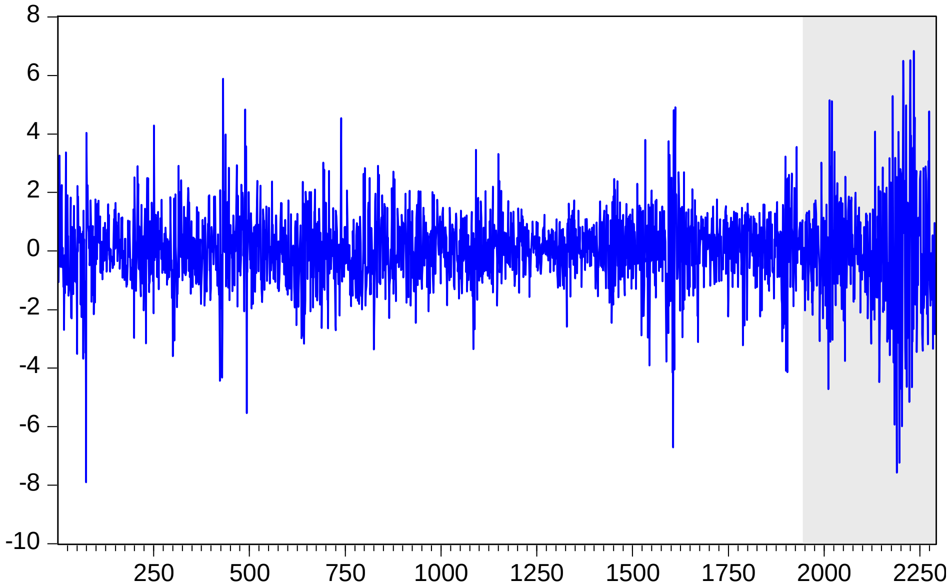
All index prices are obtained from Thomson Reuters Datastream 5.0. As the analysis is limited to local equity listings on the JSE, index prices are captured in Rand values. These prices are then converted into compounded daily returns as follows:

$$y_t = (lnP_t - lnP_{t-1}) \times 100 \quad [3.9]$$

Where: y_t is the current continuous compounded return;
P_t is the current closing index price; and
P_{t-1} is the previous day's closing index price.

The official turning points of the South African business cycle, obtained from the South African Reserve Bank (SARB) website, are used as a guideline for the financial crisis. SARB identified only one downswing since 2000, beginning in December 2007 and ending in August 2009. However, since the stock market leads the business cycle (Goodspeed, 2009:21), 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 11/10/2007 – will represent the start of the downturn. Similarly, the trough in the cycle – as indicated by the ALSI on 03/03/2009 – will represent the end of the downturn. A graphical plot of ALSI returns is provided in Figure 3.1. The shaded area, representing the period during the financial crisis, indicates a considerable increase in the volatility of returns during the downturn in the market. Graphical plots for individual sectors are included in Figure A1 of the Appendix.

FIGURE 3.1: ALL-SHARE INDEX



Notes: Shaded area represents period during the financial crisis

The motivation behind choosing daily data is that the stock market reacts very quickly to new information. Lower frequency data, such as weekly or monthly data, do not capture the changes that occur within a day and thus distort these market reactions (Chinzara and Aziakpono, 2007:9). The EMH, introduced by Fama (1965:383), suggests that efficient markets react promptly to new information. Low frequency data can thus slow down and distort such reactions.

One of the problems linked to using daily data is that of distortions arising from non-trading days. Such days usually occur on public holidays, which result in the stock market being closed. There are several ways to deal with this problem of non-trading. Karolyi (1995:12) accounts for a holiday by adding a dummy variable. An alternative approach, as followed by Glezakos, Kaligosfiris and Merika (2007), is to calculate a realistic price through simulation. There is, however, no guarantee that this price would have been realised had the stock market been open. A more appropriate solution, therefore, is to follow Chinzara and Aziakpono (2009) and Chang, Nieh and Wei (2006) by removing the non-trading days completely. Removing these days should not have a significant effect on the empirical findings due to the size of the data sample, and is therefore also done in this study.

Several sub-sectors could not provide return data for the entire sample period. Individual analysis of the following sub-sectors was therefore not possible: Household Goods and Home Consumption, Leisure Goods, Personal Goods, Tobacco, and Technological Hardware and Equipment. There are two explanations for this lack of data: either there were no price changes for the shares included in the index, or there were no shares listed on the JSE for an extensive period of time. Both explanations indicate that these sub-sectors are characterised by low levels of liquidity, suggesting that they have relatively low market capitalisations compared to the remaining sub-sectors. Excluding them from the analysis is thus not expected to have a major bearing on the returns or volatilities of their respective sectors.

3.4.2 *A priori* expectations

A summary of the a priori expectations is provided in Table 3.1. The 9 sectors are split according to whether they are expected to be cyclical ($\beta > 1$) or defensive ($\beta < 1$). The theoretical background behind sector classifications, which is discussed in Section 2.2, will not be repeated. The Oil and Gas sector, which includes Oil and Gas producers, can be classified under a larger energy industry. This industry, according to Goodspeed (2009:21), is cyclical ($\beta > 1$) and thus expected to experience a greater increase in volatility during the financial crisis than the overall market. In terms of mean returns, a cyclical industry should outperform the market index before a downturn, but fall below the market during the downturn (Goodspeed, 2009:23). The same reaction can be expected for the cyclical Technology and Industrial sectors. Technology includes Software and Computer Services and Technology Hardware and Equipment. Industrials include Construction and Materials, General Industrials, Electrical Equipment, Industrial Engineering, Industrial Transport and Support Services.

Pharmaceuticals and Telecommunications, on the other hand, are renowned defensive industries ($\beta < 1$) (Goodspeed, 2009:21). The Health Care sector is made up of two sub-sectors: Health Care Equipment and Services, and Pharmaceuticals and Biotechnology. Telecommunications is made up of Fixed-line and Mobile Telecommunications. As defensive industries experience relatively stable earnings (Mahan, 1965:69), these sectors are expected to experience a smaller increase in volatility than the market during the financial crisis. In contrast to cyclical industries, the mean returns of these defensive industries are expected to be lower than the market before the downturn, but exceed the market index during the downturn.

The defensive nature of the remaining four sectors is less clear cut. Basic Materials comprises of Chemicals, Forestry and Paper, Industrial Metals and Mining. Bodie ***et al*** (2005:590) argue that basic industries such as gold and timber perform well at the upper turning point of the business cycle. The high rate of inflation that characterises this phase has less of an impact on these industries. In spite of this, a downward phase is characterised by low demand for goods and services, which is accompanied by a fall in inflation. It is thus anticipated that although these basic industries – that constitute the bulk of Basic Materials – may initially outperform the market, they will fail to do so for the majority of the downturn. Basic Materials is therefore expected to prove cyclical ($\beta > 1$) with respect to its volatility and mean return.

Financials includes Banks, Life Insurance, Non-Life Insurance, Equity Investment Insurance and General Financials. According to Goodspeed (2009:21), banks are cyclical in nature, whereas the defensive insurance sub-sectors are less affected by market volatility. In general, financial shares are credit sensitive and only begin to rise with a recovery of the economy and loan demand (Goodspeed, 2009:22). The financial sector therefore cannot be classified as defensive, but is instead expected to prove cyclical ($\beta > 1$).

The Consumer Goods sector comprises of Automobile and Parts, Beverages, Food Producers, Household Goods and Home Consumption, Leisure Goods, Personal Goods and Tobacco. Bellehumeur (2008:1) suggests that household goods are defensive since they are predominantly things we cannot live without. While motor vehicles and household goods are cyclical, Goodspeed (2009:21) argues that Beverages, Food Producers and Tobacco are all defensive industries. Since the majority of sub-sectors are thought to be defensive, the Consumer Goods sector as a whole is expected to act defensively ($\beta < 1$) during the sample period.

TABLE 3.1: EXPECTED BETA VALUES FOR VARIOUS SECTORS

β > 1	**β < 1**
Oil and Gas	Consumer Goods
Basic Materials	Healthcare
Industrials	Telecommunications
Consumer Services	
Financials	
Technology	

Finally, Consumer Services is made up of Food and Drug Retailers, General Retailers, Media and Travel and Leisure. According to Goodspeed (2009:21), Retailers, Media and Transport are all cyclical industries, whereas only Food and Drug Retailers is defensive in nature. Consumer Services is thus expected to prove cyclical ($\beta > 1$).

3.5 Summary

In this chapter, an analytical framework is set out to analyse the returns and volatilities of various equity indices on the JSE. The frameworks for two stationarity tests are firstly discussed, namely the ADF and KPSS tests. Several models used for measuring volatility are then specified. These models fall into two groups: the CAPM beta and the univariate GARCH models. The CAPM beta is firstly simplified to exclude the risk-free rate of interest. An additional beta is then calculated for comparative purposes. This second beta, known as the volatility ratio (β^*), excludes the correlation between an index and the market. The GARCH model is then discussed together with two of its extensions, namely the GJR GARCH and the EGARCH models. The mean and variance equations for each of these models are specified, followed by a description of how they are used to examine conditional volatility. The data are finally discussed, including the source and properties of the return series used, issues with the data, and the *a priori* expectations for each index. This analytical framework is now applied to the returns series to achieve the goals of the study, as set out in Chapter one.

CHAPTER 4: RESULTS

4.1 Introduction

Having reviewed the relevant theoretical and empirical literature, set out the analytical framework and identified the *a priori* expectations, this chapter sets out to achieve the major objective of the study. That is, to determine empirically whether defensive sectors have acted defensively during the recent financial crisis. Moreover, sectors will be ranked according to their performances and an attempt will be made to explain why they have each acted in such a manner.

This chapter is divided into five sections. Section 4.2 analyses the stationarity of the data using the ADF and KPSS tests. Section 4.3 discusses the descriptive statistics, focusing primarily on mean returns and standard deviations. Using the CAPM beta and volatility ratio, Section 4.4 analyses the volatility of sector returns with respect to the market index. Section 4.5 investigates conditional volatility using the GARCH model and two of its extensions, the EGARCH and GJR GARCH models. Two key aspects of volatility are analysed, namely asymmetric volatility and the persistence of volatility to shocks in the economy. Finally, Section 4.6 summarises the chapter.

4.2 Stationarity

The results from the ADF and KPSS tests for the sectors being analysed are reported in Table 4.1. The ADF test results suggest that the null hypothesis of a unit root can be rejected for all series at level terms. With the exception of Consumer Services and Technology, which were integrated of order one for the period before the financial crisis, the KPSS test indicates similar results. These two sectors were differenced once to ensure stationarity. All other series were stationary at level.

TABLE 4.1: SECTOR STATIONARITY

	Before Crisis		During Crisis		Sample Period	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
ALSI	-41.538	0.389	-17.572	0.157	-45.024	0.216
Healthcare	-41.917	0.206	-16.752	0.242	-44.933	0.138
Telecom	-39.427	0.427	-14.962	0.182	-44.144	0.217
Consumer Goods	-43.210	0.209	-19.179	0.055	-47.284	0.092
Consumer Services	-37.233	0.055*	-17.260	0.079	-41.557	0.503
Financials	-40.217	0.497	-14.822	0.065	-44.071	0.311
Oil & Gas	-40.008	0.064	-18.567	0.248	-45.110	0.096
Industrials	-40.556	0.338	-18.089	0.109	-44.516	0.287
Basic Materials	-41.100	0.129	-16.864	0.248	-44.009	0.227
Technology	-38.137	0.072*	-17.806	0.071	-42.100	0.466

Notes: ADF 1% critical value = -3.434 and the KPSS 1% critical value = 0.739

Series that are stationary at 1st difference are indicated by a *

Subsector results are displayed in Table A1 in the Appendix

4.3 Descriptive Statistics

A summary of the descriptive statistics for the entire sample period and the two sub-periods are provided in Tables 4.2, 4.3 and 4.4, respectively. These statistics include the sample mean, median, maximum value, minimum value, standard deviation, skewness, kurtosis and Jacques-Bera test (with its p-value) for each return series.

An initial observation from Table 4.2 is that the defensive sectors, renowned for relatively stable performance, actually outperform the market and several cyclical sectors over the entire sample period. For instance, Consumer Goods, Healthcare and Telecom experience average daily returns of 0.037%, 0.047% and 0.054% respectively, which are above the market average of 0.034% and well above those of the cyclical Technology (-0.075%) and Financials (0.009%) sectors. The standard deviations of returns also question the true defensiveness of certain sectors. The defensive Telecommunications (2.306) sector had the highest standard deviation, suggesting it experienced the most volatility. Industrials (1.262) and Financials (1.325) experienced the lowest levels of volatility, even lower than the defensive Healthcare (1.368) and Consumer Goods (1.908) sectors. These findings already question the defensive and cyclical reputations of certain sectors. However, since the sub-period before the financial crisis is considerably longer than the crisis itself, not too much will be read from these performances until each sub-sector has been analysed in isolation.

The difference between maximum and minimum daily returns provides a further indication of sector volatility. These values suggest that after Technology (minimum of -20.799% and maximum of 11.625%), the sector with the most extreme values is the defensive Telecommunications industry, experiencing a minimum daily return of -10.986% and a maximum of 19.650%. The sector with the least extreme daily returns is Healthcare, with a minimum of -6.050% and a maximum of 6.281%, which, surprisingly, is not followed by renowned defensive industries, but instead by Consumer Services (minimum of -7.624% and maximum of 6.407%) and Financials (minimum of -6.925% and maximum of 6.170%).

TABLE 4.2: DESCRIPTIVE STATISTICS - ENTIRE SAMPLE PERIOD

	ALSI	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil & Gas	Technology	Telecom
Mean	0.034	0.048	0.037	0.023	0.009	0.047	0.043	0.052	-0.075	0.054
Median	0.063	0.095	-0.001	0.070	0.006	0.070	0.075	0.036	-0.039	0.054
Maximum	6.834	11.162	14.212	6.407	7.150	6.281	6.985	11.434	11.625	19.650
Minimum	-7.897	-11.811	-7.886	-7.624	-6.925	-6.050	-11.438	-10.644	-20.799	-10.986
Std. Dev.	1.367	1.904	1.908	1.168	1.325	1.368	1.262	2.122	2.223	2.306
Skewness	-0.201	-0.118	0.404	-0.560	-0.007	-0.002	-0.372	0.087	-0.742	0.290
Kurtosis	6.491	7.757	7.087	6.562	5.974	5.086	8.057	6.399	10.868	7.471
Jarque-Bera	1178.814	2165.361	1656.738	1331.068	844.354	415.356	2494.009	1105.799	6119.297	1940.456
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 4.3: DESCRIPTIVE STATISTICS - BEFORE FINANCIAL CRISIS

	ALSI	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil & Gas	Technology	Telecom
Mean	0.068	0.092	0.060	0.048	0.045	0.058	0.080	0.077	-0.057	0.079
Median	0.096	0.135	0.016	0.099	0.047	0.080	0.100	0.047	-0.029	0.082
Maximum	5.889	6.810	13.352	5.078	6.170	6.281	6.357	8.256	11.625	19.650
Minimum	-7.897	-7.428	-7.886	-7.624	-6.925	-6.050	-11.438	-8.701	-20.799	-9.996
Std. Dev.	1.181	1.544	1.892	1.050	1.165	1.302	1.168	1.794	2.211	2.116
Skewness	-0.284	-0.178	0.266	-0.918	-0.062	-0.071	-0.553	-0.040	-0.792	0.298
Kurtosis	6.066	4.766	6.414	7.950	6.085	5.333	9.704	5.026	11.241	8.443
Jarque-Bera	787.095	262.760	966.656	2256.512	771.876	442.350	3738.004	332.857	5700.972	2427.335
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 4.4: DESCRIPTIVE STATISTICS - DURING FINANCIAL CRISIS

	ALSI	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil & Gas	Technology	Telecom
Mean	-0.159	-0.199	-0.087	-0.112	-0.196	-0.017	-0.165	-0.085	-0.177	-0.084
Median	-0.168	-0.409	-0.158	-0.234	-0.299	-0.022	-0.281	-0.106	-0.116	-0.264
Maximum	6.834	11.162	14.212	6.407	7.150	6.037	6.985	11.434	10.207	13.465
Minimum	-7.581	-11.811	-7.439	-5.533	-6.653	-5.005	-5.635	-10.644	-13.623	-10.986
Std. Dev.	2.118	3.244	1.988	1.680	1.985	1.694	1.682	3.418	2.293	3.165
Skewness	0.108	0.126	1.088	0.158	0.260	0.220	0.193	0.257	-0.487	0.314
Kurtosis	4.172	4.731	10.382	3.445	3.841	3.923	4.336	4.182	9.091	4.497
Jarque-Bera	20.604	44.394	858.698	4.311	14.187	15.164	28.028	24.099	551.699	38.214
Probability	0.000	0.000	0.000	0.116	0.001	0.001	0.000	0.000	0.000	0.000

With the exception of Consumer Goods, Oil and Gas, and Telecom, which were positively skewed, all sector returns were negatively skewed. Not only are positively skewed returns more desirable, but Omran (2007:804) argues that some investors will pay a premium for positive skewness. The distributions of all sectors are characterised by positive excess kurtosis, showing evidence of fat tails. The sector with the lowest level of kurtosis was Healthcare (5.086), well above the benchmark of 3 which is described as leptokurtic relative to normal (Chinzara and Aziakpono, 2009:43). These fat tails imply that the distribution of returns in all the indices contained extreme values, suggesting that the series were not normally distributed. Finally, the high values of the Jarque-Bera (JB) statistic provided further evidence that the null hypothesis of normality could be rejected for all indices, in contradiction with the EMH.

Table 4.3 provides the summary statistics for the period before the financial crisis, characterised by an upturn in the stock market cycle. The mean returns of cyclical industries should theoretically outperform those of defensive industries during such a phase. Basic Materials and Industrials experienced the highest returns for this period, with mean daily returns of 0.092% and 0.08%, respectively. These sectors were followed by the defensive Telecom (0.079%) sector, which surprisingly exceeded the average daily return of the market index (0.068%). The mean returns for the defensive Consumer Goods (0.06%) and Healthcare (0.058%) sectors fell below that of the market, but exceeded several cyclical sectors, including Financials (0.045%) and Technology (-0.057%).

In contrast to an upturn in the market, defensive sectors are expected to outperform cyclical sectors during a downward phase of the stock market cycle. The descriptive statistics for such a downturn are provided in Table 4.4, which represents the period during the financial crisis. As expected, the average daily returns of the defensive sectors top the list. In contrast with the findings of Bellehumeur (2008), who reported Pharmaceuticals to have performed the worst in the U.S. during the financial crisis, Healthcare (-0.017%) experienced the highest mean returns. Telecommunications (-0.084%) and Consumer Goods (-0.087%), the remaining defensive sectors, ranked second and fourth respectively. While there is no contesting the fact that these sectors have acted defensively by outperforming their cyclical counterparts, it must be noted that all three sectors experienced negative mean returns during the period. This initial finding already questions their usefulness as an investment tool against other investment alternatives.

The effect of the financial crisis on mean returns is summarised in Table 4.5, which ranks the sectors based on the change in average daily returns for the two sub-periods. The sector affected least by the financial crisis is that of Healthcare, which experienced a decrease in mean return of 0.076%. Surprisingly, Technology was ranked second with a fall of 0.12%. A look at graphical plots of sector returns (in Figure A1 of the Appendix) reveals that Technology experienced a large amount of volatility in the early stages of the sample period. These volatile returns were no doubt caused by the bursting of the dot-com bubble in the U.S. in 2000. This volatility in the Technology sector would have weakened the effect of the recent financial crisis on the sector's overall volatility during the sample period. The defensive Consumer Goods (-0.146%) and Telecommunications (-0.163%) sectors ranked third and sixth respectively, proving significantly more defensive than the market index (-0.228%). Basic Materials (-0.291%) proved to be the least defensive sector, having experienced the highest mean returns before the crisis and the lowest during the crisis.

The dispersion of index returns, indicated by the difference between maximum and minimum values, also questions the true defensiveness of certain indices. Healthcare proved the most defensive during the financial crisis, with a maximum daily return of 6.037% and a minimum of -5.005% (see Table 4.4). Telecommunications (maximum of 13.465 and minimum of -10.986), on the other hand, experienced the most extreme returns during the financial crisis.

Table 4.6 provides a summary of the standard deviations (σ) of the sector returns before and during the financial crisis. In addition, the table indicates each sector's change in standard deviation ($\Delta\sigma$) for the two periods. As mentioned previously, defensive sectors can withstand the shocks of market volatility and are therefore not expected to experience a major change in standard deviation as a result of the financial crisis. Consumer Services (1.05), Financials (1.165) and Industrials (1.168) experienced the lowest volatility before the crisis, well below the renowned defensive sectors. Healthcare's standard deviation of 1,302 surprisingly exceeded that of the market (1.181). The defensive Telecommunications (2.116) and Consumer Goods (1.892) sectors experienced the second and third highest volatility, respectfully. In accordance with the findings of Black *et al* (2002) and He and Kryzanowski (2007), Technology (2.211) proved the most volatile.

Consumer Services experienced the lowest level of volatility during the financial crisis, with a standard deviation of 1.68 units. The standard deviations of Healthcare (1.694) and Consumer Goods (1.988) fell below that of the market index (2.118), moving them up to third and fifth place, respectfully, relative to other sectors. Telecommunications (3.165) again failed to show any defensive characteristics, with its level of volatility being exceeded by only Basic Materials (3.244) and Oil and Gas (3.418). Surprisingly, Technology was affected the least by the financial crisis, experiencing a standard deviation increase of only 0.083 units. Consumer Goods and Healthcare proved the second and third most defensive with increases in volatility of 0.096 and 0.392 units, respectively. Telecommunications experienced an increase in standard deviation of 1.049 units, again exceeding the market index (0.937). Basic Materials proved the least defensive, experiencing a standard deviation increase of 1.7 units. These figures question the true defensive nature of the Telecommunications sector, as well as the cyclical nature of Technology and Consumer Services. As mentioned, the bursting of the dot-com bubble in 2000 could explain the apparent defensive performance of Technology. However, the defensive and cyclical performances of Consumer Services and Telecommunications, respectfully, warrant further investigation.

TABLE 4.5: MEAN RETURNS

Before Crisis		During Crisis		Change	
Sector	Mean (%)	Sector	Mean (%)	Sector	Δ Mean (%)
Basic Materials	0.092	Healthcare	-0.017	Healthcare	-0.076
Industrials	0.080	Telecom	-0.084	Technology	-0.120
Telecom	0.079	Oil & Gas	-0.085	Consumer Goods	-0.146
Oil & Gas	0.077	Consumer Goods	-0.087	Consumer Services	-0.160
ALSI	0.068	Consumer Services	-0.112	Oil & Gas	-0.162
Consumer Goods	0.060	ALSI	-0.159	Telecom	-0.163
Healthcare	0.058	Industrials	-0.165	ALSI	-0.228
Consumer Services	0.048	Technology	-0.177	Financials	-0.242
Financials	0.045	Financials	-0.196	Industrials	-0.245
Technology	-0.057	Basic Materials	-0.199	Basic Materials	-0.291

TABLE 4.6: STANDARD DEVIATIONS

Before		During		Change	
Sector	σ	Sector	σ	Sector	$\Delta\ \sigma$
Consumer Services	1.050	Consumer Services	1.680	Technology	0.083
Financials	1.165	Industrials	1.682	Consumer Goods	0.096
Industrials	1.168	Healthcare	1.694	Healthcare	0.392
ALSI	1.181	Financials	1.985	Industrials	0.515
Healthcare	1.302	Consumer Goods	1.988	Consumer Services	0.630
Basic Materials	1.544	ALSI	2.118	Financials	0.820
Oil & Gas	1.794	Technology	2.293	ALSI	0.937
Consumer Goods	1.892	Telecom	3.165	Telecom	1.049
Telecom	2.116	Basic Materials	3.244	Oil & Gas	1.624
Technology	2.211	Oil & Gas	3.418	Basic Materials	1.700

4.4 CAPM betas and relative volatilities

Having determined the level of stand-alone volatility for each equity index from the descriptive statistics, we now estimate the volatility of index returns relative to variation in the market return. As discussed in Chapter 3, the CAPM beta measures the sensitivity of an index's return to systematic market risk, which cannot be reduced through diversification. The CAPM betas for the two sub-periods and the sample period as a whole are reported in Table 4.7 below. As mentioned earlier, a beta coefficient below one indicates that the sector has acted defensively during the period under investigation. Hence, the smaller the beta coefficient is, the more defensive the equity index. Similarly, a beta coefficient above one indicates the magnitude of the nature of a cyclical sector. Each index is then ranked according to its level of defensiveness with respect to the other indices. Finally, the effect of the financial crisis on each sector (relative to the period before the financial crisis) is indicated by calculating the difference in rankings for the two sub-periods.

The CAPM betas estimated for the entire sample period tend to differ from the *a priori* expectations set out in Chapter 3. Three of the four sectors that proved defensive (β < 1) were expected to be cyclical. Consumer Services, Industrials and Financials all proved defensive, with beta coefficients of 0.483, 0.568 and 0.704, respectfully. Healthcare (0.571) was the only defensive sector that acted in line with the *a priori* expectations. Consumer Goods (1.2) and Telecommunications (1.55) surprisingly proved cyclical (β > 1) for the whole sample period, experiencing the sixth and ninth largest beta coefficients, respectfully. As a result of the disproportionate sizes of the sub-samples, the results reported for the period before the financial crisis are very similar to those of the sample period as a whole. Consumer Services (0.45), Industrials (0.602), Healthcare (0.732) and Financials (0.748) were again the only sectors with beta coefficients of less than one. Consumer Goods (1.592), Telecommunications (1.634) and Oil and Gas (1.909) remained highly cyclical.

TABLE 4.7: CAPM BETA

	Sample Period		Before		During		Difference
	β	Rank	β	Rank	β	Rank	in Ranks
Consumer Services	0.483	1	0.450	1	0.442	2	-1
Industrials	0.568	2	0.602	2	0.493	3	-1
Healthcare	0.571	3	0.732	3	0.328	1	2
Financials	0.704	4	0.748	4	0.625	5	-1
ALSI	1.000	5	1.000	5	1.000	7	-2
Consumer Goods	1.200	6	1.592	8	0.591	4	4
Technology	1.320	7	1.565	7	0.670	6	1
Basic Materials	1.544	8	1.207	6	2.190	10	-4
Telecom	1.550	9	1.634	9	1.395	8	1
Oil and Gas	1.938	10	1.909	10	2.002	9	1

Note: 'Difference in Ranks' refers to the difference in rank between the periods before and during the financial crisis

Source: Author's estimates

Despite the surprisingly high levels of volatility experienced by several defensive sectors, not much should be read into their performances during the entire sample period. This is due to the sub-period before the crisis, representing an upturn in the stock market, being considerably longer than the sub-period representing the financial crisis. Of greater interest is the effect of the financial crisis on sector performance. Healthcare ranked as the most defensive sector during the financial crisis, with a beta of 0.328. Consumer Services (0.442) and Industrials (0.493) fell by one place each, but, contrary to *a priori* expectations, were still ranked as the second and third most defensive sectors. Consumer Goods (0.591) rose four places to rank as the fourth most defensive sector, proving extremely resilient against the financial crisis. The defensive performances of Financials (0.625) and Technology (0.670) also differed from the *a priori* expectations. In line with the findings of He and Kryzanowski (2007) in the U.S., Telecommunications again proved cyclical, questioning its reputation as a defensive industry. Its beta coefficient did, however, decline from 1.634 to 1.395, suggesting it showed some resilience during the financial crisis. The finding that only three sectors (Telecommunications, Oil and Gas and Basic Materials) experienced a beta greater than the market beta of one suggests that these indices represent a disproportionately large number of the shares listed on the JSE. A breakdown of the top ten companies listed on the JSE, in terms of market capitalisation, is available on the JSE website. Unsurprisingly, four of the top ten are mining companies and thus fall under Basic Materials. Included in the top five companies is Sasol (oil and gas producer) and the MTN Group (provider of mobile telecommunications).

The performances of several sectors can be better understood by taking a closer look at their constituent sub-sectors. Excluding Telecommunications and Oil and Gas, which are made up of only one sub-sector each, sub-sector betas are provided for all sectors in Table A1 of the Appendix. The defensive performance of Consumer Services can be explained by three of its sub-sectors contradicting finance theory. While Food and Drug Retailers acted in line with ***a priori*** expectations, the remaining cyclical sub-sectors did not. General Retailers, Media and Travel and Leisure all acted in unexpectedly defensive fashions during the financial crisis. This tends to suggest that these industries were more protected in South Africa's developing market than they were elsewhere in the world.

Two other cyclical sectors that acted defensively during the financial crisis were Financials and Industrials. Inspection of their respective sub-sectors (see Table A2 in the Appendix) provides two alternative explanations for this behaviour. While all financial sub-sectors experienced a smaller beta during the crisis relative to before the crisis, two sub-sectors in particular stand out: Non-Life Insurance (0.238) and Equity Investment Insurance (0.241). Insurance is in fact a defensive industry (Goodspeed, 2009:21), making the defensive performance of Financials considerably less surprising. Like Financials, all sub-sectors making up Industrials acted defensively during the financial crisis. The most likely explanation for this behaviour is the effect of the 2010 FIFA World Cup on the South African economy. In preparing to host the world's largest sporting event, the building of new stadiums and improved infrastructure would have undoubtedly led to steady demand in all Industrial sub-sectors.

As discussed in Chapter 3, the calculation of a CAPM beta can confound correlation and relative volatility. A simplified beta, known as the volatility ratio, focuses exclusively on the volatility of a sector relative to the market by excluding the correlation coefficient. This volatility ratio, specified as β*, is reported in Table 4.8. While the volatility ratio does not have a major effect on sector rankings, it is clear that there are fewer extreme beta values. In other words, there are fewer sectors that acted very defensively (β^* close to zero) as well as fewer that proved very cyclical (β^* close to 2 or higher).

Only three sectors proved defensive for the entire sample period. Consumer Services (0.855), Industrials (0.923) and Financials (0.969) all had betas of less than one. Interestingly, all three of these sectors are renowned for acting in a cyclical manner. The three defensive sectors, on the other hand, all acted in a cyclical fashion. Healthcare (1.001) experienced a relative volatility that was only fractionally greater than the market beta of one. Consumer Goods (1.395) ranked as the seventh most defensive sector, whilst Telecommunications (1.687) proved to be the least defensive. These results again proved very similar to those for the period before the financial crisis. Consumer Services (0.889) proved the most defensive, whilst only Technology (1.872) proved more cyclical than Telecommunications (1.792).

During the financial crisis, Consumer Services (0.793) proved to be the most defensive sector, again questioning the expectation for it to act in a cyclical manner. In line with the findings of the CAPM beta, the defensive performances of General Retailers and Travel and Leisure (see Table A2 in the Appendix) are responsible for Consumer Services acting defensively. Industrials (0.794) proved the second most defensive, which can in part again be attributed to the impact of the FIFA World Cup. Healthcare (0.8) moved up two places to rank as the third most defensive sector. Contrary to ***a priori*** expectations, Financials (0.937) proved marginally defensive during the financial crisis.

TABLE 4.8: VOLATILITY RATIO

	Sample period		**Before**		**During**		**Difference**
	β*	Rank	β*	Rank	β*	Rank	**in Ranks**
Consumer Services	0.855	1	0.889	1	0.793	1	0
Industrials	0.923	2	0.989	3	0.794	2	1
Financials	0.969	3	0.987	2	0.937	4	-2
ALSI	1	4	1	4	1	6	-2
Healthcare	1.001	5	1.102	5	0.800	3	2
Basic Materials	1.393	6	1.307	6	1.532	9	-3
Consumer Goods	1.395	7	1.602	8	0.939	5	3
Oil and Gas	1.552	8	1.519	7	1.614	10	-3
Technology	1.626	9	1.872	10	1.083	7	3
Telecom	1.687	10	1.792	9	1.494	8	1

Note: 'Difference in Ranks' refers to the difference in rank between the periods before and during the financial crisis

Source: Author’s estimates

Consumer Goods, which proved to be the fifth most defensive sector, showed a substantial amount of resilience during the financial crisis. Its volatility ratio of 1.602 before the crisis declined to 0.939 during the crisis. Taking a closer look at its constituent subsectors (in Table A3 of the Appendix), this resilience to the crisis was achieved despite the cyclical performance of Automobiles and Parts, suggesting that the defensive Food Producers had a far greater weighting in terms of market capitalisation. As expected, Technology (1.083), Basic Materials (1.532) and Oil and Gas (1.614) all proved cyclical, showing greater levels of volatility than the market. Despite a lower beta than before the crisis (an indication of defensive performance), Telecommunications (1.494) again proved cyclical during the financial crisis.

4.5 Conditional volatilities

Having established the defensive classification of the sectors during the financial crisis, this section investigates their conditional volatilities. As discussed in Chapter 3, a distribution of financial returns typically displays fat tails, volatility clustering and leverage effects. Three models are used to capture these properties: the GARCH, GJR GARCH and EGARCH models.

4.5.1 The mean equation

The mean equation specified in equation (3.5) of Chapter 3 was estimated for each sector during each sub-period and the sample period as a whole. As mentioned in Chapter 3, these equations took the form of ARMA (p, q) models. Provided each model showed no sign of autocorrelation, the number of lags with the lowest SIC and AIC values was selected. The results were then tested for ARCH effects to determine whether volatility had been adequately captured. The ARCH LM F-statistics from the sectors' respective mean equations are reported in Table 4.9.

The large LM statistics indicate that the majority of sectors show significant evidence of ARCH effects, implying that those sectors' mean equations did not adequately capture volatility. The only sectors that failed to show evidence of ARCH effects were Consumer Goods and Industrials, for the period during the financial crisis. Since the mean equation adequately captures the volatility of these two sectors, the estimation of GARCH models is no longer appropriate. For the remaining series, the GARCH model and its extensions are estimated to determine which is most appropriate for the data.

TABLE 4.9: AUTOCORRELATION TEST FOR THE MEAN EQUATION

	Whole sample			**Before Crisis**			**During Crisis**		
	(*p*,*q*)	ARCH LM	p-value	(*p*,*q*)	ARCH LM	p-value	(*p*,*q*)	ARCH LM	p-value
ALSI	(3,3)	123.104	0.000	(4,3)	103.867	0.000	(0,3)	3.412	0.065
Basic Materials	(2,2)	143.613	0.000	(2,2)	56.928	0.000	(1,3)	3.293	0.070
Consumer Goods	(2,2)	36.061	0.000	(2,2)	57.925	0.000	(1,1)	0.000	0.992
Consumer Services	(1,0)	157.799	0.000	(1,1)	155.806	0.000	(2,2)	4.717	0.031
Financials	(2,3)	148.159	0.000	(3,2)	201.953	0.000	(1,1)	5.511	0.020
Healthcare	(2,2)	91.260	0.000	(2,2)	140.750	0.000	(1,1)	7.258	0.008
Industrials	(1,0)	179.335	0.000	(4,4)	140.750	0.000	(1,1)	1.206	0.272
Oil & Gas	(0,1)	163.990	0.000	(0,1)	23.287	0.000	(2,2)	12.013	0.001
Technology	(1,0)	194.150	0.000	(1,1)	190.682	0.000	(3,3)	8.207	0.005
Telecom	(5,4)	159.392	0.000	(3,2)	91.022	0.000	(1,2)	13.05735	0.000

Source: Author's estimates

4.5.2 Univariate GARCH models

The results from the univariate GARCH (1, 1), GJR GARCH (1, 1, 1) and EGARCH (1, 1, 1) models are reported in Tables 4.10, 4.11 and 4.12, respectively. For all three models, the coefficient ω represents the intercept, or average level of volatility, whilst α and β are the squared residual and squared variance coefficients, respectively. These coefficients generally proved highly significant for all three models. Only for the sub-period during the financial crisis, were results for the EGARCH and GJR GARCH models less significant for certain sectors. The intercept coefficient (ω) for both Consumer Services and Financials proved insignificant under the GARCH model. Under the GJR model, α proved insignificant for Basic Materials during the crisis, whilst both ω and α proved insignificant for Consumer Services. For the E-GARCH specification, the ω and α coefficients were the least significant during the financial crisis. Telecommunications experienced an insignificant α, whilst Basic Materials, Healthcare and the All-share index experienced both insignificant ω and α coefficients under the E-GARCH model.

The sum of the α and β coefficients is high in all models, suggesting that volatility is highly persistent. Thus, shocks tend to die off slowly. In the EGARCH model, however, the stationarity condition ($\alpha + \beta < 1$) is violated, since the sum of α and β exceeds one for nearly every sector. For this reason, the EGARCH model was no longer used in this study and the GJR model is preferred for capturing asymmetric behaviour. Using the remaining two models, the persistence of volatility for each sector was compared to that of the market. The results from the GARCH model (Table 4.10) suggest that volatility persistence was very similar between sectors for all periods. Only two sectors experienced meaningfully lower volatility persistence than the market (0.987) during the financial crisis, namely Telecommunications (0.955) and Consumer Services (0.966). This would suggest that these sectors acted defensively to aggregate shocks during the financial crisis. In line with the findings of the CAPM and volatility ratio, Industrials also acted defensively by experiencing the lowest persistence over the full sample period.

The GJR GARCH (see Table 4.11) showed greater variation among sectors than the GARCH model. For the sample period as a whole, Industrials (0.889) experienced a considerably lower level of volatility persistence than the market (0.918). During the financial crisis, Healthcare (0.770) and Telecommunications (0.835) experienced persistence in volatility that was well below that of the market (0.905), providing further evidence of their defensive performances. In contrast, the persistence of cyclical Financials (0.953) and Technology (0.980) exceeded that of the market by some margin. One possible explanation for this finding is that these sectors receive a large amount of external financing. According to Comin and Philipon (2005:196), industries that receive a large amount of external financing are more sensitive to aggregate shocks. A second explanation is that there has been a large amount of technological innovation in the Financial and Technology sectors. Black *et al* (2002:39) argue that technological innovation has increased the efficiency of markets through more readily available information. As a result, investors tend to revise their expectations about future cash flows more regularly, leading to an increase in sector specific volatility.

TABLE 4.10: GARCH (1, 1)

	Sample Period				Before Crisis				During Crisis			
	ω	α	β	α + β	ω	α	β	α + β	ω	α	β	α + β
ALSI	0.031	0.111	0.874	0.985	0.040	0.111	0.863	0.974	0.072	0.102	0.884	0.987
Basic Materials	0.030	0.083	0.909	0.993	0.037	0.082	0.904	0.986	0.178	0.082	0.900	0.982
Consumer Goods	0.039	0.098	0.896	0.994	0.037	0.104	0.892	0.996	N/A	N/A	N/A	N/A
Consumer Services	0.033	0.128	0.851	0.979	0.052	0.146	0.807	0.953	0.102*	0.069	0.897	0.966
Financials	0.042	0.127	0.850	0.977	0.054	0.125	0.835	0.961	0.070*	0.129	0.863	0.993
Healthcare	0.038	0.060	0.920	0.980	0.047	0.062	0.909	0.971	0.032	-0.037	1.029	0.992
Industrials	0.058	0.126	0.841	0.967	0.072	0.119	0.828	0.948	N/A	N/A	N/A	N/A
Oil & Gas	0.080	0.066	0.915	0.981	0.141	0.064	0.892	0.956	0.179	0.076	0.909	0.985
Technology	0.035	0.101	0.898	0.999	0.012	0.053	0.946	0.999	0.145	0.216	0.778	0.994
Telecom	0.098	0.105	0.878	0.983	0.137	0.109	0.859	0.968	0.444	0.060	0.895	0.955

Note: * indicates insignificance at the 10% level

Source: Author's estimates

A second comparison analysed was the effect of the financial crisis on volatility persistence in each sector. No major changes were recorded by the standard GARCH model during the financial crisis. In contrast, the GJR GARCH did record noticeable changes in volatility persistence between the two sub-periods. Financials and Consumer Services showed clear evidence of increasing persistence, an attribute which could be expected of cyclical industries. These findings contrast sharply with those of the CAPM and volatility ratio, which found both sectors to have acted defensively during the crisis. Four sectors showed lower persistence in volatility during the crisis. Surprisingly, two of these were Basic Materials and Oil and Gas, renowned cyclical industries. The two sectors that showed the largest decreases in volatility persistence were Healthcare and Telecommunications, suggesting that these defensive industries remained the most resilient to shocks in the economy. These findings do not contrast much with those of Malik and Hasan (2004), who found that shocks in the health and consumer sectors in the U.S. die off the fastest.

TABLE 4.11: GJR GARCH (1, 1, 1)

	Sample Period					Before Crisis					During Crisis				
	ω	α	β	α + β	γ	ω	α	β	α + β	γ	ω	α	β	α + β	γ
ALSI	0.036	0.035	0.883	0.918	0.122	0.043	0.042	0.868	0.910	0.118	0.050	-0.041	0.946	0.905	0.186
Basic Materials	0.036	0.044	0.912	0.956	0.065	0.044	0.059	0.900	0.959	0.045	0.171	-0.021*	0.937	0.915	0.138
Consumer Goods	0.037	0.040	0.912	0.952	0.082	0.072	0.101	0.835	0.935	0.093	N/A	N/A	N/A	N/A	N/A
Consumer Services	0.036	0.049	0.863	0.912	0.112	0.051	0.055	0.831	0.886	0.123	0.091*	0.015*	0.908	0.923	0.100
Financials	0.042	0.046	0.867	0.913	0.128	0.051	0.034	0.860	0.894	0.134	0.068	0.086	0.867	0.953	0.090*
Healthcare	0.038	0.056	0.920	0.976	0.007*	0.047	0.062	0.909	0.971	0.000*	0.514	0.116	0.654	0.770	0.109*
Industrials	0.065	0.036	0.853	0.889	0.136	0.097	0.042	0.809	0.851	0.142	N/A	N/A	N/A	N/A	N/A
Oil & Gas	0.076	0.029	0.921	0.950	0.065	0.126	0.034	0.900	0.935	0.053	0.146	-0.068	0.962	0.893	0.207
Technology	0.038	0.071	0.902	0.973	0.045	0.015	0.046	0.941	0.987	0.023	0.119	0.201	0.779	0.980	0.039*
Telecom	0.116	0.080	0.872	0.952	0.053	0.139	0.088	0.861	0.949	0.036	0.623	-0.075	0.910	0.835	0.232

Note: * indicates insignificance at the 10% level

Source: Author’s estimates

TABLE 4.12: EGARCH (1, 1, 1)

	Sample Period					Before Crisis					During Crisis				
	ω	α	β	α + β	γ	ω	α	β	α + β	γ	ω	α	β	α + β	γ
ALSI	-0.130	0.172	0.978	1.150	-0.082	-0.142	0.186	0.967	1.153	-0.083	0.014*	0.022*	0.981	1.003	-0.144
Basic Materials	-0.118	0.175	0.982	1.156	-0.044	-0.130	0.201	0.966	1.167	-0.035	-0.016*	0.075*	0.981	1.056	-0.098
Consumer Goods	-0.111	0.170	0.981	1.151	-0.061	-0.122	0.187	0.979	1.166	-0.056	N/A	N/A	N/A	N/A	N/A
Consumer Services	-0.137	0.177	0.966	1.143	-0.075	0.143	0.009	-0.970	-0.961	-0.006*	-0.067	0.117	0.970	1.087	-0.080
Financials	-0.147	0.197	0.971	1.168	-0.093	-0.144	0.189	0.958	1.147	-0.096	-0.136	0.234	0.964	1.198	-0.072*
Healthcare	-0.089	0.133	0.978	1.111	-0.009	-0.091	0.134	0.974	1.108	-0.003*	-0.010*	0.047*	0.976	1.023	-0.026*
Industrials	-0.135	0.191	0.950	1.140	-0.092	-0.141	0.198	0.923	1.121	-0.099	N/A	N/A	N/A	N/A	N/A
Oil & Gas	-0.071	0.116	0.987	1.102	-0.040	-0.059	0.120	0.971	1.090	-0.032	0.079	0.111	0.982	1.093	-0.137
Technology	-0.138	0.206	0.986	1.192	-0.034	3.154	0.018	-0.997	-0.979	-0.006	-0.214	0.329	0.975	1.303	-0.030*
Telecom	-0.101	0.178	0.976	1.154	-0.040	-0.112	0.197	0.968	1.164	-0.028	0.090	0.045*	0.944	0.989	-0.125

Note: * indicates insignificance at the 10% level

Source: Author's own estimates

The coefficient of asymmetry (γ), which is specified in the GJR GARCH and EGARCH models, is used to test for asymmetric sector volatility. In the GJR GARCH, γ must be positive and significant for leverage effects to be present. This implies that a negative shock will have a greater effect on volatility than a positive shock of the same magnitude. With the exception of Healthcare, there is evidence of leverage effects in all sectors for the whole sample period. The same can be said for the sub-period before the financial crisis. Fewer sectors experienced leverage effects during the financial crisis, namely Basic Materials, Consumer Services, Oil and Gas, Telecommunications and the all-share index. As suggested by Chinzara and Aziakpono (2007:37), this could result from lower share prices in these sectors increasing firms' debt-to-equity ratios, leaving investors less certain about future cash flows. Alternatively, investor sentiment can be blamed for the widespread panic shared by investors after experiencing losses.

4.6 Summary

In this chapter, the performances of various sectors are evaluated based on their returns and volatilities during the recent financial crisis. In doing so, each sector's performance is categorised as being either defensive or cyclical. As expected, the defensive Healthcare, Telecommunications and Consumer Goods sectors all experienced greater mean returns than the market during the financial crisis. These three sectors were surprisingly joined by Oil and Gas and Consumer Services, which also outperformed the market index.

Sector volatilities relative to the market were estimated using the CAPM beta and volatility ratio. Both models provided similar results, suggesting that Healthcare, Consumer Services and Industrials acted the most defensively during the financial crisis. Consumer Goods and Financials also proved less volatile than the market, while Technology experienced conflicting results.

Having dropped the EGARCH model from the analysis, conditional volatilities were estimated using the GARCH and GJR GARCH models. Industrials, Telecommunications, Healthcare and Consumer Services all displayed defensive characteristics by proving the most resilient to shocks in the economy. Leverage effects, which indicate cyclical behavior, were reported for Basic Materials, Oil and Gas, Consumer Services and, surprisingly, Telecommunications.

CHAPTER 5: CONCLUSION

5.1 Summary of study and conclusion

The study analysed the performances of nine sectors on the JSE based on their returns and volatilities during the recent financial crisis. This was done to classify them as either defensive or cyclical, depending on their performances in relation to the market index, with a view to providing investment advice to South African investors. In doing so, the study managed to achieve its primary goal; that is, to determine whether historically defensive sectors on the JSE have – with respect to the market – proven to be defensive during the recent financial crisis.

A background to defensive investments was firstly provided by discussing the relevant theoretical literature. This included a review of Business Cycle Theory, MPT, market efficiency and asset pricing models. Pertinent empirical literature was then reviewed, focusing on studies that analyse and compare the performances of different sectors. A common finding was that Healthcare and Consumer Staples lived up to their reputations as defensive industries. Contrary to theoretical literature, however, Telecommunications failed to act defensively in several studies. While a number of empirical studies have compared the descriptive statistics and CAPM betas of different sectors, there are few that have focused on the South African market. Furthermore, there appears to be no documented literature that used GARCH models to analyse the conditional volatilities of South African sectors. This study aimed to fill these gaps.

In order to classify each South African sector as defensive or cyclical, its performance was evaluated based on both its returns and the volatility of those returns. Defensive industries are renowned for stable performance. They are therefore expected to experience returns that are below that of the market during a bull market, but outperform the market during a bear market. Surprisingly, Consumer Goods, Healthcare and Telecommunications not only experienced higher mean returns than the market during the financial crisis, but they did so for the sample period as a whole. In contrast to the *a priori*, Oil and Gas and Consumer Services also outperformed the market during the financial crisis. The volatilities of these returns had to be considered before any conclusions could be made.

Two groups of related models were used to determine sector volatilities. The first included the CAPM beta and volatility ratio, both of which estimate volatility in relation to a market index. Due to the disproportionate sizes of the sub-samples, greater emphasis was placed on performances during the financial crisis than for the sample period as a whole. Both models provided similar results, suggesting that Healthcare, Consumer Services and Industrials acted the most defensively during the financial crisis. While Healthcare is a renowned defensive industry, Industrials and Consumer Services are not. The stable performance of Industrials can be attributed to the effect of hosting the 2010 FIFA World Cup, whereas the defensive performances of Consumer Services' sub-sectors suggest that they were isolated from the volatility of the global market. Consumer Goods and Financials also proved less volatile than the market, while Technology experienced conflicting results. The defensive Consumer Staples and Insurance sub-sectors can be attributed to the defensive performances of Consumer Goods and Financials, respectively. Lastly, the volatility of Technology's returns appears to have been distorted by the effect of the dot-com bubble in 2000. However, a graphical plot of its returns (see Figure A1 in the Appendix) indicates a large amount of volatility throughout the sample period, suggesting it acted in a cyclical fashion.

The second group of models used to analyse sector volatility was the GARCH models. Having dropped the EGARCH model from the analysis, conditional volatilities were estimated using the GARCH and GJR GARCH models. Healthcare, Industrials, Telecommunications and Consumer Services all proved defensive, displaying lower levels of volatility persistence than the market index. With the exception of Telecommunications, these findings concur with those of the CAPM and volatility ratio. In contrast, Technology and Financials experienced greater persistence in volatility than that of the market. Technological innovation and the efficient flow of information in these sectors are attributed to their cyclical performances. Leverage effects were reported for Basic Materials, Oil and Gas, Telecommunications and Consumer Services, indicating that negative returns in these sectors had a greater impact on volatility than positive returns of the same magnitude.

In conclusion, the cyclical performances of Basic Materials, Technology and Oil and Gas were in line with both theoretical and empirical literature. Financials experienced mixed results, with Banks and Insurance sub-sectors acting in cyclical and defensive fashions, respectively. There thus appears to be insufficient evidence to conclude that Financials acted defensively during the financial crisis. Industrials and Consumer Services, on the other hand, did act defensively during the financial crisis. Despite Consumer Services experiencing leverage effects, the weight of the findings suggest that both these sectors failed to act in line with the ***a priori***.

Of the three traditionally defensive sectors, only Healthcare and Consumer Goods acted defensively during the financial crisis. The bulk of findings suggest that Telecommunications failed to act defensively during the financial crisis. Despite conflicting with finance theory, its cyclical performance is in line with several empirical studies in the U.S. In contrast, Healthcare consistently proved to be the most defensive sector, suggesting that the pharmaceutical industry is highly insensitive to the state of the economy. It is safe to conclude that since the timing of a recession is difficult to predict, defensive securities can be a useful investment tool for protection against adverse movements in the stock market.

5.2 Areas for future research

One limitation of this study is that it ignores dividend payouts. As a result, returns are simply calculated as changes in prices from one period to the next. As defensive shares are normally associated with large, well established companies, dividends could have significant effects on mean returns. Further research could thus more accurately measure company performance by perhaps assuming that dividend payouts are reinvested back into their respective companies.

A second area for further research would be to analyse the effects of macroeconomic factors on individual sectors. Such factors could include economic growth, commodity prices (such as gold and oil), inflation and the exchange rate. An understanding of the impacts such variables have on a sector's returns could further explain its defensive or cyclical performance.

Thirdly, this study focused on one financial crisis. It is recommended that future studies include as many upturns and downturns in the market as possible. This would produce more robust results and could provide sound investment advice over a longer horizon. Such research will no doubt be possible as more data on the South African market becomes available.

Finally, while several sectors acted defensively by outperforming the market, none of them experienced positive mean returns during the financial crisis. An area for further research would be to compare the mean returns of defensive shares to those of alternative investment vehicles, such as Rand Hedge funds or Inverse funds that move in an opposite direction to the market. This would give a more complete indication of the value of defensive shares as an investment tool.

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APPENDIX

TABLE A1: CAPM BETA

	Before		During		Whole period	
	β	Rank	β	Rank	β	Rank
ALSI	1	18	1	22	1	18
Consumer Goods						
Auto &parts	0.318	2	0.113	1	0.343	3
Beverages	0.991	17	0.733	16	0.895	16
Food producers	0.398	5	0.266	5	0.348	4
Consumer Services						
Fd & Drug Retailers	0.596	11	0.398	6	0.522	9
General Retailers	0.453	8	0.451	9	0.494	8
Media	1.316	21	0.842	17	1.196	21
Travel & Leisure	0.387	4	0.243	4	0.342	2
Healthcare						
Equipment & Svs	0.617	12	0.398	7	0.545	11
Pharm & Bio	0.702	13	0.429	8	0.604	13
Financials						
Banks	1.110	20	0.933	20	1.045	19
Life Insurance	1.019	19	0.959	21	1.048	20
Non-life Insurance	0.423	7	0.238	2	0.353	5
General Financials	0.948	16	0.852	18	0.936	17
Eq inv Insurance	0.490	10	0.241	3	0.408	7
Basic Materials						
Forrestry & Paper	1.891	23	1.230	23	1.650	23
Mining	2.010	24	2.319	24	2.119	24
Technology						
Software	1.716	22	0.670	15	1.424	22
Industrials						
Con & Mat	0.414	6	0.895	19	0.582	12
Electro Eq	0.337	3	0.515	12	0.405	6
General Inds	0.755	15	0.481	10	0.654	14
Inds Eng	0.212	1	0.489	11	0.313	1
Inds Transport	0.474	9	0.589	13	0.523	10
Support Svs	0.706	14	0.635	14	0.724	15

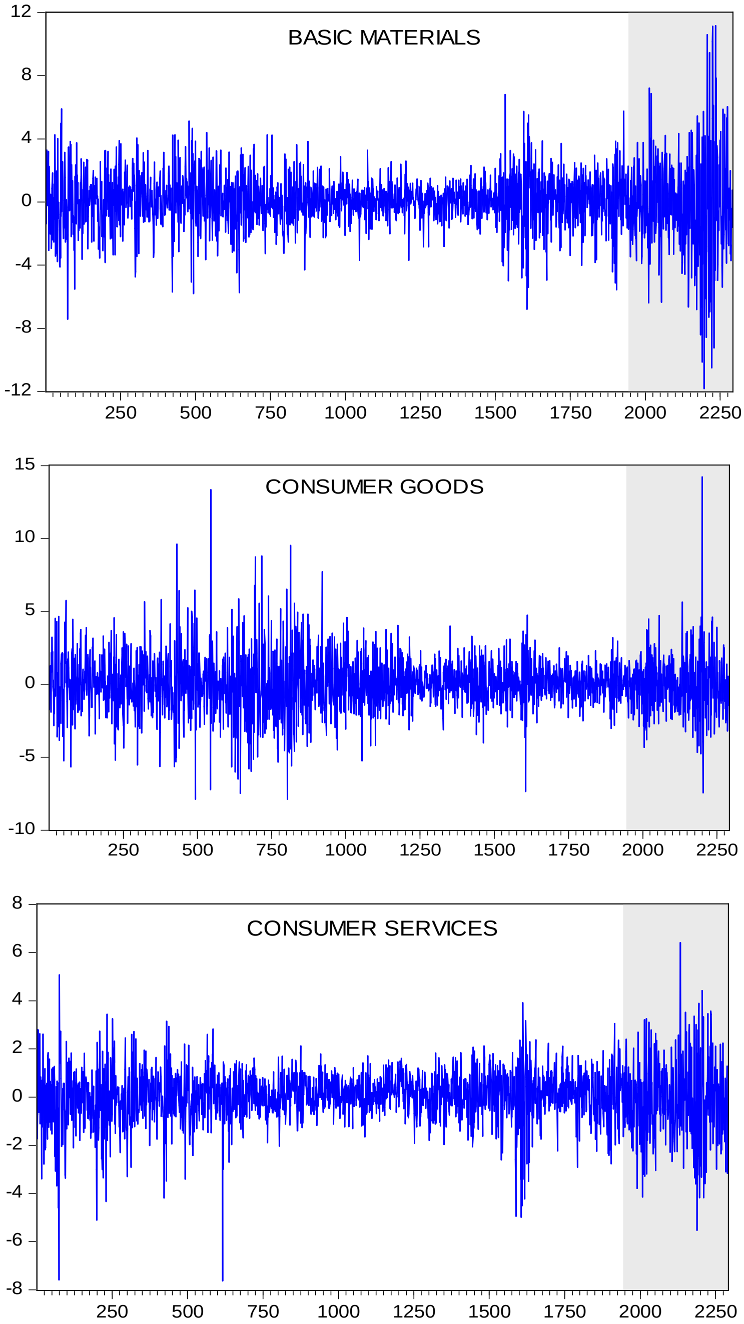
Source: Author's estimates

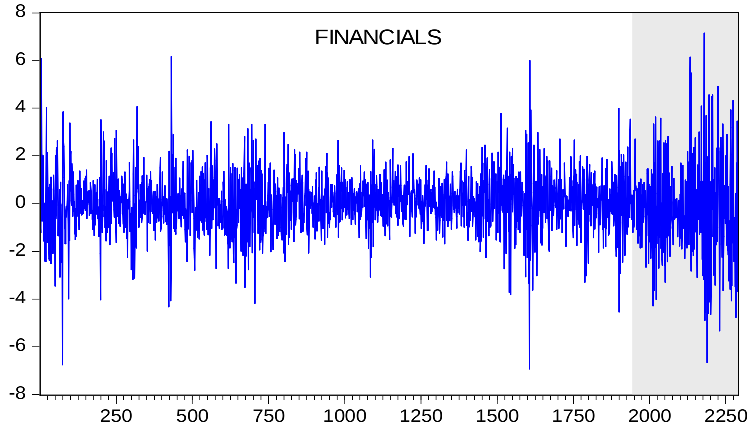
TABLE A2: VOLATILITY RATIO

	Before		During		Whole period	
	β*	Rank	β*	Rank	β*	Rank
ALSI	1	4	1	8	1	4
Consumer Goods						
Auto &parts	1.393	19	3.140	24	2.193874	24
Beverages	1.355	17	1.129	13	1.276	17
Food prod	0.874	1	0.703	1	0.815	1
Consumer Services						
Fd &dg retailers	1.216	13	0.915	6	1.114	11
General retailers	1.035	5	0.873	4	0.979	3
Media	1.718	22	1.182	18	1.542	21
Travel &leis	1.144	10	0.753	2	1.019	5
Healthcare						
Eq &svs	1.348	16	0.911	5	1.206	14
Pharm &bio	1.657	21	1.130	14	1.484	19
Financials						
Banks	1.363	18	1.224	19	1.313	18
Life ins	1.251	14	1.234	20	1.245	16
Non-life ins	1.098	9	1.022	10	1.069	9
Gen fin	1.256	15	1.174	17	1.226	15
Eq inv ins	1.036	6	1.160	16	1.082	10
Basic Materials						
For &paper	1.919	23	1.523	22	1.785	23
Mining	1.507	20	1.582	23	1.534	20
Technology						
Software	1.985	24	1.083	12	1.709	22
Industrials						
Con &mat	0.992	3	1.152	15	1.055	8
Electro eq	0.933	2	1.020	9	0.968	2
Gen inds	1.155	11	0.852	3	1.053	7
Inds eng	1.065	8	1.283	21	1.152	13
Inds transport	1.057	7	0.990	7	1.036	6
Support svs	1.179	12	1.077	11	1.142	12

Source: Author's estimates

FIGURE A1: GRAPHICAL PLOTS OF INDIVIDUAL SECTORS

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0
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-4
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-8
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750
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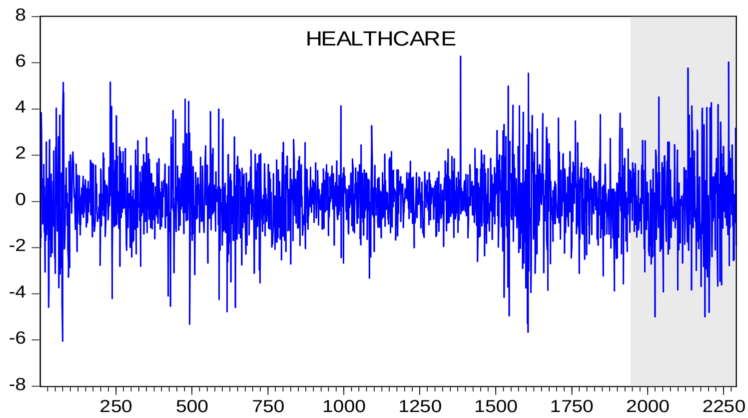
1750
2000
2250


HEALTHCARE
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6
4
2
0
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-4
-6
-8
250
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1000
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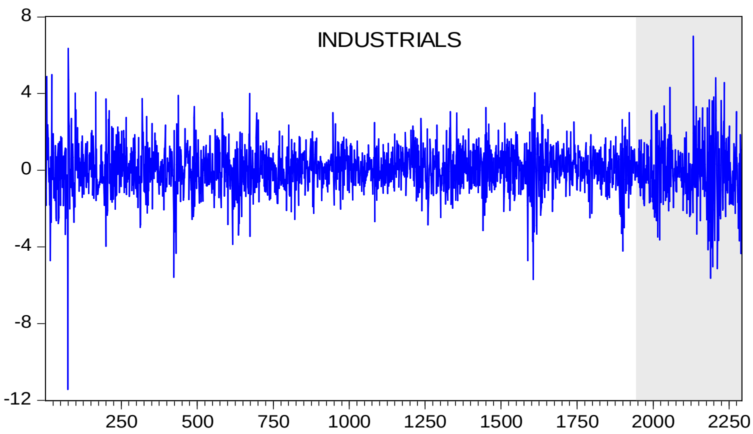
2250


INDUSTRIALS
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0
-4
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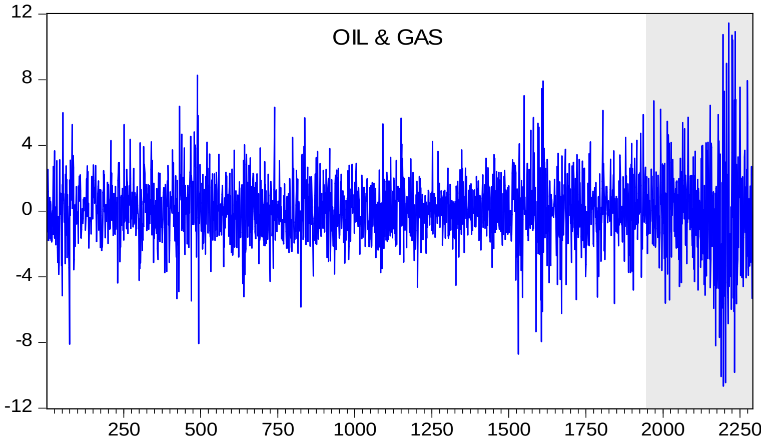
500
750
1000
1250
1500
1750
2000
2250


OIL & GAS
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-4
-8
-12
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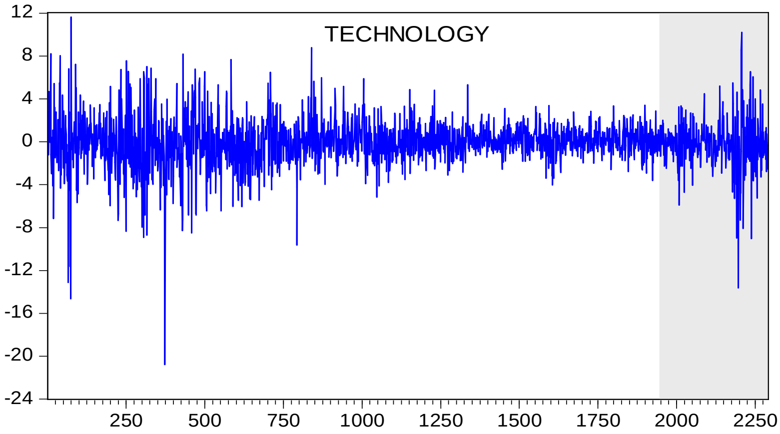
500
750
1000
1250
1500
1750
2000
2250


TECHNOLOGY
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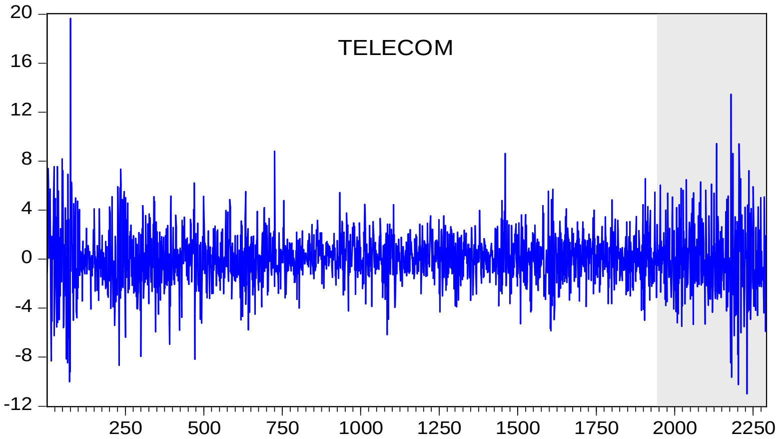
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