THE DAY-OF-THE-WEEK EFFECT AS A RISK FOR HEDGE FUND MANAGERS

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Potchefstroom

2005

ACKNOWLEDGEMENTS

First and foremost, I thank God Almighty for the opportunity and capability to complete this dissertation. Without His grace, it would not have been possible.

I further acknowledge everybody that contributed to the completion of this dissertation, and in particular the people mentioned below for providing assistance during the completion of this study.

- my supervisor, professor Paul Styger, for his leadership and guidance throughout the duration of this dissertation. I am grateful for his friendly and prompt feedback and his knowledgeable input regarding every aspect of this dissertation;

- my assistant supervisor, professor Jan du Plessis, for his various contributions with regards to the empirical work done in this dissertation. A special word of thanks for his friendly and enthusiastic assistance and particularly for the large amount of time he invested in this dissertation;

- my parents, for their continuous interest in my work as well as their love and support;

- my friends, for their friendship and support through the good and the difficult times;

- Sabrina, for her moral support and assistance with the language editing of this dissertation.

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2005

ABSTRACT

The day-of-the-week effect is a market anomaly that manifests as the cyclical behaviour of traders in the market. This market anomaly was first observed by M.F.M. Osborne (1959). The literature distinguishes between two types of cyclical effects in the market: the cyclical pattern of mean returns and the cyclical pattern of volatility in returns.

This dissertation studies and reports on cyclical patterns in the South African market, seeking evidence of the existence of the day-of-the-week effect. In addition, the dissertation aims to investigate the implications of such an effect on hedge fund managers in South Africa.

The phenomenon of cyclical volatility and mean returns patterns (day-of-the-week effect) in the South African All-share index returns are investigated by making use of four generalised heteroskedastic conditional autoregressive (GARCH) models. These were based on Nelson's (1991) Exponential GARCH (EGARCH) models. In order to account for the risk taken by investors in the market Engle *et al*'s, (1987) 'in-Mean' (risk factor) effects were also incorporated into the model. To avoid the dummy variable trap, two different approaches were tested for viability in testing for the day-of-the-week effect. In the first approach, one day is omitted from the equation so as to avoid multi-colinearity in the model. The second approach allows for the restriction of the daily dummy variables where all the parameters of the daily dummy variables adds up to zero.

This dissertation found evidence of a mean returns effect and a volatility effect (day-of-the-week effect) in South Africa's All-share index returns data (where Wednesdays have been omitted from the GARCH equations). This holds significant implications for hedge fund managers, as hedge funds are very sensitive to volatility patterns in the market, because of their leveraged trading activities. As a result of adverse price movements, hedge fund managers employ strict risk management processes and constantly rebalance their portfolios according to a mandate, to avoid incurring losses.

This rebalancing typically involves the simultaneous opening of new positions and closing out of existing positions. Hedge fund managers run the risk of incurring losses should they rebalance their portfolios on days on which the volatility in market returns is high. This study proves the existence of the day-of-the-week effect in the South African market.

These results are further confirmed by the evidence of the trading volumes of the JSE's All-share index data for the period of the study. The mean returns effect (high mean returns) and low volatility found on Thursdays, coincide with the evidence that trading volumes on the JSE on Thursdays are the highest of all the days of the week. The volatility effect on Fridays, (high volatility in returns) is similarly correlated with the evidence of the trading volumes found in the JSE's All-share index data for the period of the study. Accordingly, hedge fund managers would be advised to avoid rebalancing their portfolios on Fridays, which show evidence of high volatility patterns. Hedge fund managers are advised to rather rebalance their portfolios on Thursdays, which show evidence of high mean returns patterns, low volatility patterns and high liquidity.

Keywords: Day-of-the-week effect, Hedge funds, EGARCH, Volatility effect, Mean returns effect.

OPSOMMING

Die "day-of-the-week effect" is 'n mark verskynsel wat manifesteer as die sikliese optrede van handelaars in die mark. Hierdie verskynsel was vir die eerste keer opgemerk deur M.F.M Osborne (1959). Die literatuur onderskei tussen twee tipes sikliese effekte in die mark: die sikliese patroon in gemiddelde opbrengste en die sikliese patroon in die volatiliteit in mark opbrengste.

Hierdie verhandeling bestudeer sikliese patrone in die Suid-Afrikaanse mark ten einde die bestaan van die "day-of-the-week effect" te bevestig in hierdie mark. Die verhandeling bestudeer ook die implikasies van hierdie sikliese patroon op verskansingsfondsbestuurders.

Die bestaan van die "day-of-the-week effect" vir Suid-Afrika word ondersoek deur gebruik te maak van vier (GARCH) modelle. Diè GARCH modelle word gepas op Suid-Afrika se Algehele aandele indeks opbrengs data. Hierdie modelle is gebaseer op Nelson (1991) se Eksponensiële GARCH (EGARCH) modelle, en sluit 'n risiko faktor in, wat die vorm van Engle *et al.* (1987) se 'in-Mean' effek aanneem. Ten einde die fop veranderlike lokval te vermy, word twee verskillende benaderings gebruik om te toets vir die "day-of-the-week effect". Die eerste vereis dat een dag uitgelaat word om te verseker dat multikolinariteit nie in die model voorkom nie. Die tweede benadering vereis dat die fop veranderlikes se parameters beperk word in so 'n mate dat hulle som nul sal wees.

Hierdie verhandeling bewys die bestaan van 'n sikliese patroon in gemiddelde opbrengste en 'n sikliese patroon in die volatiliteit in mark opbrengste ("day-of-the-week effect") vir Suid-Afrika se Algehele aandele indeks opbrengs data (waar Woensdag uitgelaat word uit die GARCH vergelykings). Omrede verskansingsfondse gebruik maak van hoë risiko investerings strategieë is hulle sensitief vir sikliese patrone in volatiliteit. Die resultate hou dus belangrike implikasies in vir verskansingsfondsbestuurders.

Ten einde groot verliese te voorkom in sulke omstandighede, implementeer verskansingsfondsbestuurders streng risikobestuur prosesse, en herbalanseer hulle hul portefeuljes op 'n gereëlde basis. Hierdie herbalanseringsproses sluit tipies die uittrede uit, en neem van posisies in die mark in. Sou verskansingsfonds bestuurders dus kies om hul portefeuljes op dae te herbalanseer waarin hoë volatiliteit in opbrengste voorkom, staan hulle die kans om groot verliese te verwesenlik.

Hierdie verhandeling bewys dat die "day-of-the-week effect" wel voorkom in Suid-Afrika. Diè resultate word verder bevestig deur die patrone in die verhandeling van aandele op die JSE tydens die studie periode. Die sikliese patroon in gemiddelde opbrengste (hoë opbrengste patroon), en die lae volatiliteit in opbrengste op Donderdae, klop met die feit dat meer aandele verhandel word op Donderdae as op enige ander dag in die week. Die volatiliteit effek (hoë volatiliteit in opbrengste) op Vrydae, korreleer ook met die hoeveelheid verhandelings in die JSE se Algehele aandele indeks. Verskansingsfonds bestuurders word dus dienooreenkomstig aangeraai om Vrydae te vermy as gevolg van die bewyse dat hoë volatiliteitspatrone op Vrydae voorkom. Hulle word aangeraai om eerder hul portefeuljes op Donderdae te herbalanseer, en so dus gebruik te maak van hoë opbrengste patrone, lae volatiliteit in opbrengste en hoë likwiditeit in die mark.

Sleutelbegrippe: "Day-of-the-week effect", Verskansingsfondse, EGARCH,
Volatiliteit effek, Gemiddelde opbrengste effek.

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CHAPTER 1

Introduction

Markets can remain irrational longer than you can remain solvent.

John Maynard Keynes
(Du Toit, 2002)

1.1 Introduction

Markets have the ability to catch the most experienced market participant off guard. Adverse market conditions have been known to ruin many a hedge fund over the past few decades, and will continue to do so in the future. Hedge funds and other investment vehicles alike have been subject to adverse and fine market conditions with various outcomes. While some hedge funds have been able to weather the storm; others have been found wanting. The name of the game is risk, and it is only the top performers that are able to survive and return their investors' money with interest year after year.

Hedge funds, in particular, have become an increasingly popular investment destination over the past few years. These alternative investment vehicles have been the focus of many debates regarding the financial crises in the South East Asian countries in 1997 (Edwards, 1999:201). While some feel that hedge funds have been the culprit behind the demise of these emerging economies, others argue that they were merely trapped in the storm alongside other investors. Times, however, have changed and investors are ever hungrier for larger returns on their investments.

Due to flexible investment strategies, sophisticated investors, limited regulatory oversight, and debatably reasonable fee structures; hedge funds have gained tremendous popularity (Liang, 2000:1). Hedge funds can be described as partnerships in which the managers are general partners and the investors are limited partners.

There are several unique features that distinguish hedge funds from traditional investment funds, and help explain the increasing popularity of hedge funds (L'habitant, 2001:2). First, due to their legal structure, hedge funds are not subject to the same level of regulation as mutual funds, and thus enjoy greater flexibility in choosing their investment strategies. Hedge funds may hold long and short positions, and they are known to make use of leverage that enables them to exploit small mispricings which are converted into gains. Leverage may be presented in various forms (Schneeweis *et al.*, 2004:5):

Gross Leverage = (Long positions + Short positions)/Net Asset Value

Net Leverage = (Long positions – Short positions)/Net Asset Value

Gross Longs = (Long positions)/Net Asset Value

As a result of these leveraged positions, hedge funds can better exploit potential market inefficiencies and seek positive abnormal returns. Hedge fund returns are less correlated to market returns than conventional investment vehicle returns, and thus provide additional diversification benefits.

Hedge funds typically focus on absolute returns instead of relative returns. They are generally incorporated offshore and operate beyond the reporting and regulatory requirements of traditional investment funds (van Royen, Kritzman & Chow, 2002:1). Hedge fund managers usually charge between 1 and 2 percent annual handling fees and 20 percent on the profits for the year. In addition, they make use of lock-up periods in order to prevent investors from liquidating their interests in the hedge fund. Lock-up periods allow managers the freedom to focus on the realisation of long-term strategies.

The hedge fund industry appears to be growing at an immense rate. It is difficult to assess the number of hedge funds operating in the industry due to the largely unregulated and sometimes opaque nature of hedge fund operations. The reason it is so difficult to assess the exact number of active hedge funds in the market is that some hedge funds close down whilst others are born. It is estimated that approximately 5 percent of hedge funds close every year; moreover, there are some indications that the

closure rate may be rising. TASS Management Limited estimates that since the beginning of 2000, hedge funds have attracted an additional $ 250 billion in new investments (FSA, 2005:13).

With the industry growing and investors looking to diversify their portfolios, hedge funds have come to the attention of institutional investors as well. These investors include pension plans, endowments and foundations. More institutional investors are looking to diversify their portfolios with investments in vehicles featuring flexible investment strategies, which hedge fund advisers make use of in pursuing positive returns, in both declining and rising securities markets. Furthermore, investors are also keen to invest in absolute return strategies (U.S. Securities and Exchange Commission, 2003:11).

The result of this new found interest in hedge funds could be of great consequence to the average, middle-income investor. Once institutional investors invest a portion of their portfolio in a hedge fund, the pensioner or medical aid member is effectively investing in the hedge fund themselves. Therefore it is important for these role-players to be aware of all the inherent risks concerning these investment vehicles. Hedge fund managers should be equally concerned with these risks and manage them accordingly. Since the growth in the industry has become more proliferative, the drive to ensure greater returns has become more competitive.

With competition becoming fiercer and markets as volatile as ever, the hedge fund manager faces a variety of risks. One of these is disguised in the form of market anomalies. The day-of-the-week effect is such a market anomaly and manifests as the cyclical behaviour of traders in the market. This market anomaly was first observed by M.F.M. Osborne (1959), a physicist who applied the concept of Brownian motion to the U.S. stock market. The day-of-the-week effect has since been a hot topic amongst academics and market participants alike.

Market anomalies have been researched by a number of academics over the past four decades. Their studies cover countries around the world and include the effects of these anomalies on stock, futures, securities and various other markets.

This dissertation will explore the existence of the day-of-the-week effect in South Africa's All-Share index returns, and the impact of this market anomaly on the profit making ability of the hedge fund managers. The problem statement and the aims of the dissertation will be discussed in more detail below. A detailed chapter outline will then follow, in order to elucidate the progression of this dissertation.

1.2 Problem Statement

Due to the rapid development rate of the financial sector across the globe, and the constant increase in market activity, the inherent risks pertaining to this sector remain an ever-present factor. Exposure to risk is a reality of participating in the market: indeed no profit comes without risk. Despite this there is no need to take unnecessary risks in the quest for profits. To avoid excessive risks, hedge fund managers (and other portfolio managers) are bound to abide by a specific mandate that specifies the level of risk to be maintained. In order to maintain this mandate, the hedge fund manager will rebalance the portfolios within the hedge fund to attain the desired level of risk, without surrendering the benchmark profit margin.

Hedge funds are exposed to various additional risks in comparison with other investment vehicles such as mutual funds.[1] As has been previously mentioned, these risks may take the form of market anomalies, which can be described as any event that occurs on a regular basis and impacts on market variables (Boudreaux, 1995:15). Among the better-known anomalies are *the weekend effect, the January effect* and the day-of-the-week effect (Monday effect). If one takes hedge funds' investment strategies into consideration, it follows that market anomalies (the day-of-the-week effect in particular) might pose an additional risk for the hedge fund manager in South Africa.

In summary, the problem statement consists of the following two questions: First, the day-of-the-week effect present in the South African market, and furthermore, if this market anomaly does indeed exist in the South African market, what impact does it have on and what risks does it hold for hedge fund managers?

1.3 Aims of the dissertation

The aims of this dissertation are twofold, with the outcomes of the second depending on the results of the first:

First, to determine the existence of the day-of-the-week effect (a specific market anomaly) in the South African market by making use of various volatility measurement tools.

Second, to better understand and describe the impact of the day-of-the-week effect on hedge fund managers in the South African market. Since hedge funds are active in a wide range of trading activities, this particular market anomaly may have a negative impact on the hedge fund's performance and therefore hold considerable risk. It is furthermore to be determined if hedge fund managers can, in some way, benefit from the day-of-the-week effect.

1.4 Chapter Outline

Chapter 2 explores the hedge fund industry, more specifically its history, the current face of the industry and some prominent investment strategies. This chapter outlines the growth of the hedge fund industry from its origin in 1949 up to the present. The focus then shifts to some of the most prominent hedge fund investment strategies. After discussing the various investment strategies, the South African hedge fund industry is discussed.

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[1] More will be said about these additional risks in chapter 5.

Chapter 3 enquires into, and discusses four of the most important risk measurement tools and thereafter briefly describes the risk management process within an 'average' hedge fund. The discussion of the risk measurement tools commences with Beta, and then goes on to explain Value at Risk (VAR); correlation and volatility; and liquidity risk. Next, the risk management process within a hedge fund is detailed, in order to form a more holistic picture of the impact that risks (such as market anomalies) have on hedge funds. The comprehension of this risk management process will assist in the explanation of the manner in which hedge fund managers should manage the day-of-the-week effect in the South African market.

Chapter 4 outlines a model, with which the existence of the day-of-the-week effect is tested in the South African All-Share index returns data. The chapter begins with a brief outline of the history and documentation of the day-of-the-week effect. The focus then shifts to an in-depth study of relevant literature pertaining to the models with which the day-of-the-week effect is tested. The data and methodology used for modelling the day-of-the-week effect are then discussed in detail. Chapter 4 concludes with the final results of the tests performed on the South African All-Share index returns data and makes suggestions to hedge fund managers, with regards to managing the day-of-the-week effect. This discussion will also touch on the risk management process in hedge funds, with reference to the impact of the day-of-the-week effect on hedge fund managers. A short discussion on a possible reason for high mean returns, and low volatility in returns patterns on Thursdays is also given.

Chapter 5 concludes this dissertation with a brief summary of both hedge funds, the risk management process in hedge funds, and the day-of-the-week effect. Conclusions are also drawn with regard to the results of day-of-the-week effect patterns in the South African market, and its influence on hedge fund managers.

CHAPTER 2

Overview and History of Hedge Funds

The hedge fund industry has become one of the fastest growing segments of the
investment community since the 1990's

Bailey, Li and Zhang (2004)

2.1 Introduction

This chapter provides the background information necessary to place one in a position
to assess whether or not the day-of-the-week effect holds a significant risk for the
hedge fund manager. Firstly a definition of hedge funds is provided, which is then
followed by the history and establishment of these unique investment vehicles. The
focus then shifts towards the present day, providing insight into the current position
and dynamics of the hedge fund industry. The different types of hedge funds are also
defined. Finally, the position of hedge funds in South Africa is discussed with
reference to the size of the industry, the regulatory position and the prospects for the
growth of this industry in South Africa.

This chapter serves as a preamble to chapter 3 which discusses various measures of
risk and risk management in general, as well as those pertaining to hedge funds in
particular.

2.2 Defining Hedge Funds

The term hedge fund generally refers to private investment vehicles that seek above-
average returns through active portfolio management (Agarwal & Naik, 1999:3).
Hedge funds tend to be skill-based, investment strategies that attempt to obtain returns
based on the unique skill or strategy of the trader (Anjivel *et al.*, 2001:2). According to
the International Monetary Fund (IMF) (2000:78), hedge funds are often defined as
pooled investment vehicles that are privately organised and administered by

professional investment managers. These managers, known as hedge fund managers, are responsible for managing the hedge fund according to a consistent mandate. The hedge fund's mandate determines the risk profile and profit margin of the fund (U.S. Securities and Exchange Commission, 2003:129).

Because hedge funds have long been exempted from regulatory control, they were not widely available to the public, but only to the select and wealthy few (McCrary, 2002:7). This is, however, no longer the case. As the allocation of funds by corporate and public pension funds to hedge funds, as a defined asset class, is a recent phenomenon, a more stringent approach to hedge funds' risk management process is needed (Kao, 2001:2).

Hedge funds are alternative investment vehicles that 'hedge' risks by taking both long and short positions in the market (FTSE, 2005:2). By offsetting long positions in undervalued stocks, with short positions in overvalued stocks, a market neutral environment is created. This 'hedged' position allows capital to be leveraged,[2] whilst enabling hedge fund managers to make large wagers with limited resources (HedgeCo.net, 2005). Hedge funds not only concentrate their efforts on taking opposite positions in the market, but also make use of other return-enhancing tools. These tools include the buying and selling of derivatives, and making use of leverage and arbitrage (Hedge World, 2003:1). It is the use of these return-enhancing tools that allows hedge funds to achieve such outstanding results.

The establishment of hedge funds is discussed below with specific reference to their origin and progression over the past five decades. A broad overview of the general classifications of hedge funds strategies is also provided.

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[2] It should be noted that there is a wide variety of interpretations of the term *leverage* and that, consequently, a wide variety of methodologies is used for its measurement. More will be said about leverage in subsequent chapters.

2.3 The Establishment of Hedge Funds

In order to comprehend completely the impact of an anomaly such as the day-of-the-week effect on the management of a hedge fund, a brief history of hedge funds is necessary. This section serves as an introduction to the background of the hedge funds and is followed by their development and their current status in the financial sector.

Although the term 'hedge fund' was coined only years later, the first investment vehicle of its kind was born shortly after the end of the Second World War. In 1949, Alfred Winslow Jones, a sociologist employed at Fortune magazine, was working on assignment, which investigated forecasting methods on the stock market (HedgeCo.net, 2005).

After receiving his Doctorate in Sociology from Columbia University in 1941, Jones became a reporter for Fortune Magazine. Whilst researching and writing an article for Fortune on the current trends in investing and market forecasting, he founded an alternate (and superior) system for managing money (FTSE, 2005:4). In 1949, he raised $ 100,000 ($ 40,000 of his own) and started the first long-short-fund which would later be called a 'hedge fund' (Gabelli, 2003:1).

Alfred Jones' new investment formula involves the 'hedging' of his long stock positions by selling short overvalued stocks, thereby creating a leveraged exposure that is market neutral (Edwards, 1999:190). Another alternative investment tool, at the time, was to make use of leverage to increase the potential return on his new partnership's assets. By making use of these speculative tools, Jones' investment firm quickly grew into a lucrative business venture. By 1952 Jones had decided to transform his general partnership into a limited partnership, and introduced a 20 percent incentive fee on the realised profits for himself, as managing partner. In addition, Jones specified that specific limited partnerships, if structured correctly, are to be exempted from regulatory control under the Investment Company Act of 1940. This exemption allows managers to utilise techniques, such as leverage and short-selling which typically bind other mutual funds and investment companies.

By 1966 Alfred Winslow Jones was responsible for the four most common characteristics of the classic hedge fund: short selling, leverage, incentive fees, and shared risk (Gabelli, 2003:1).

Up until 1966, Jones kept his investment strategies secret, as many successful investors have done before him. After being in secret operation for seventeen years, Jones' success was finally revealed in a 1966 Fortune Magazine article titled "The Jones that nobody can keep up with" (Gabelli, 2003:2). In addition to detailing Jones' unique investment strategy, the article publicised that his partnership had out performed the best performing mutual fund that year by 44 percent; and the best five-year performing mutual fund at the time by 85 percent, net of all fees (FTSE, 2005:5).

It was this article that initiated the rapid growth of the hedge funds. Soon, talented professional investors were willing to sacrifice their large salaries for profit participation in the portfolios they managed. The newly-formed investment schemes, that made use of Jones' new hedging strategy, quickly found wealthy individuals seeking better investment returns. By 1968, the amount of hedge funds grew to approximately 200 (FTSE, 2005:3). It was also during this time that investment greats, such as George Soros, Warren Buffett and Michael Steinhardt joined the hedge fund world (FTSE, 2005:2).

The next section considers the development of hedge funds as investment vehicles from the 1960s.

2.4 The Chronicles of Hedge Funds

An exposition of the development of the hedge fund industry is imperative to this dissertation, in facilitating the comprehension of the investment strategies of the hedge fund industry, and thus the risks involved when investing in these investment vehicles. This section thus briefly delineates the development of hedge funds and provides a short account of the current status of hedge funds.

After Jones' initial success in the investment world, many other investors attempted to imitate his investment strategies. Many of these new hedge fund managers, however, quickly drifted away from Jones' original principles once they realised that allocating a portion of their assets to short sales impacted negatively on performance returns, during the boom markets of the late 1960s. The result was a movement away from such investments.

This lack of insurance began to catch up with these investors as markets turned in 1969/70 and eventually saw many simply close their doors as the bear market turned into a crash in 1973 (Gabelli, 2003:2). By this time many new entrants to this sector were discouraged by the recent failures of many prominent hedge funds. Even as markets began to improve towards the end of the 1970s investors and investment companies alike remained sceptical.

By 1984, only 68 hedge funds could be identified (Gabelli, 2003:2). This trend, however, was at its end and exceptional growth in the mid-80s and early 90s saw an estimated total of over 1 300 hedge funds in operation by 1988 (McCrary, 2002:5).

Despite hedge funds being blamed for the near collapse of the Long Term Capital Market in 1998, as well as the Asian Crises just a year before, these institutions continued to grow in numbers (U.S. Securities and Exchange Commission, 2003:133).

Because some hedge funds close down while others are born, it is difficult to pinpoint the exact figures. As indicated in Figure 2.1, today, approximately 8 000 hedge funds are in operation worldwide, including survivors such as George Soros' Quantum Fund (HedgeCo.net, 2005). It is estimated that hedge funds currently manage some $ 1 trillion and that this figure is still growing (see figure 2.1).

FIGURE 2.1   THE GROWTH OF THE HEDGE FUND INDUSTRY FROM 1949 - 2005
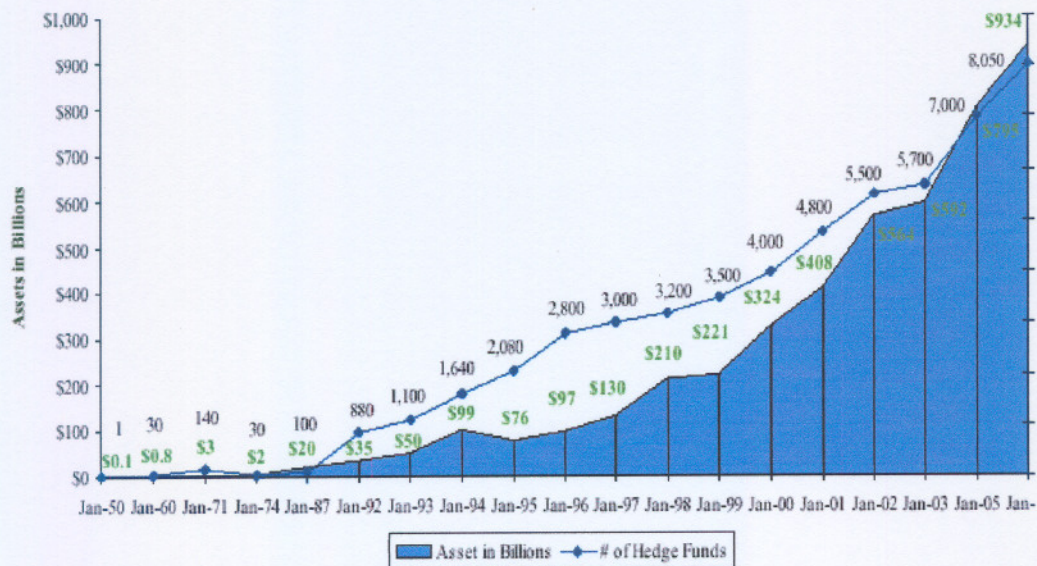
(Hennessee Group LLC, 2005a)

The following section explores the current state of the hedge fund industry, and provides an overview of some prominent hedge fund strategies.

2.5 Hedge Funds Today

2.5.1 Introduction

The hedge fund industry has changed tremendously over the past five decades in many aspects. As hedge funds became more popular, the regulatory aspects surrounding these investment vehicles have in turn become more rigorous. Since hedge funds are no longer reserved for the rich, hedge fund managers are forced to avoid excessive risk wherever possible.

This section looks at the current hedge fund industry with the aim of explaining the risk environment within which risk funds managers find themselves. The risks themselves will be discussed in more detail in chapter 3.

2.5.2 The Current State of the Worldwide Hedge Fund Industry

As previously mentioned, it is estimated that currently 8 000 hedge funds are managing almost $ 1 trillion in assets (HedgeCo.net, 2005). The hedge funds of today not only make use of the original long short mix that Jones introduced in 1949, but also make use of additional profit-enhancing tools. George Soros' Quantum Fund, for example, has made huge profits by speculating with currencies. Others make use of futures contracts, mortgage bonds and commodities to name but a few. Today's fund managers also have the added advantage of complex statistical models that allow them to eliminate more risks than their predecessors fifty years ago (HedgeCo.net, 2005).

It therefore follows that the investor base has broadened in the past few years to include private pension funds, state pension funds, corporations and insurance companies (McCrary, 2002:49). As indicated in figure 2.2 below, individual investors do, however, still hold the biggest share in hedge funds, followed by Fund of funds, Corporate Institutions and Pension funds.

FIGURE 2.2   THE DISTRIBUTION OF MONEY BETWEEN THE VARIOUS HEDGE FUND INVESTORS WORLDWIDE
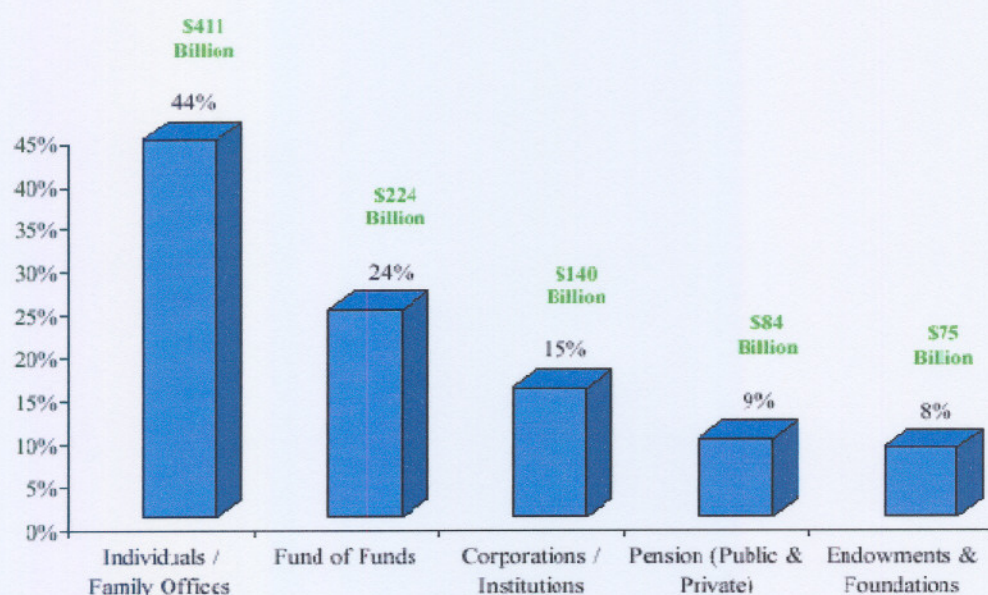
(Hennessee Group LLC, 2005a)

In recent times, large institutional investors have been reported in the press as partially shifting their allocation from traditional investments (Beta) to alternative investments (Alpha). Large American universities such as Yale have already anticipated this new trend by investing more than 50 percent of their portfolio alternatively (Moix & Bacmann, 2003:2).

Alpha refers to the factors that affect the performance of an individual stock or investment manager's skill in selecting a particular stock. Alpha is also used as a measurement of an investment manager's return that cannot be attributed to the market. It thus shows the difference between a fund's actual return and its excess return, adjusted for risk that an active investment manager seeks to add, relative to a given market index (Brittain *et al.*, 2005:1).

Beta represents the risk and return produced by a market index or asset class and indicates how sensitive an investment has been to market movements. An investment with greater sensitivity to changes in the market will have a greater Beta (Brittain *et* al., 2005:1).

Traditional investments (Beta) thus have portfolios that are market linked and of which its performance is based on market movements alone. Alternative investments (Alpha) aim to earn profits over and above the market returns based on the investment manager's skills.

There are various reasons for the shift from Beta investments to Alpha investments. Traditional investments (Beta) are usually targeted to deliver a performance related to a given benchmark. Since Alpha investment strategies were long exempt from strict regulatory constraints, these investment vehicles had the freedom to use alternative strategies to achieve profit margins that exceeded that of the benchmark related Beta investments.

The emergence of legal constraints, heavy risk management and new accounting rules are also to blame for the shift that institutional investors have made from Beta investments to Alpha investments.

Unlike Beta investment strategies, Alpha investment strategies are focussed on absolute returns. It is due to this objective and the fact that hedge funds are allowed to go short, that they were able to outperform mutual funds over the last decade. Many hedge funds have attempted to capture market inefficiencies, resulting in 'pure' Alpha strategies (Moix & Bacmann, 2003:2).

Since there is increased interest in the hedge fund industry, some investment banks have been setting up hedge funds within their asset management groups, whilst reducing their proprietary trading activity. There are, however, still risks involved and investors are likely to seek the stability and reduced risk profiles of Fund of funds.[3] Another encouraging aspect is that there has been a further differentiation within the hedge fund industry. Some hedge funds are becoming more liquid and registered hedge funds are reducing their minimum initial investment amounts (Anson, 2003:8). Others are decreasing their lock-up periods and lowering redemption frequencies.[4] This allows more investors to invest in hedge funds.

Because of the increasing interest in alternative investment strategies, this sector has had an increasing demand for experts to head hedge funds. Skills and alignment of interest are the cornerstones of designing Alpha-generating strategies, and private equity and hedge fund managers are indeed well-educated and very experienced. Hedge fund managers in particular have spent an average of 22 years in the profession. These managers often invest in their own strategies: up to 70 percent of these managers have invested their own money in their strategies as incentive to perform well (Moix & Bacmann, 2003:2).

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[3] Fund of funds is a hedge funds strategy that entails the management of several individual hedge funds under one manager, called a Fund of funds manager. A complete discussion on this hedge fund strategy is given in section 2.6.11.

[4] The typical lock-up period for hedge funds is usually 24 months. During this period the hedge fund will not permit any withdrawals or additional investments. (Bailey et al., 2004:8).

Since emphasis is placed on knowledge, many managers are attempting to keep the level of transparency of their investment methods low. Transparency, however, is of limited value without liquidity. Because hedge funds limit the amount of investors many of them are rarely open for additional investment. Many hedge fund managers also require that investors invest their money for a specific period of time. Investors are thus not allowed to disinvest (withdraw their money from the hedge fund), and are penalised if they do so. In cases where disinvestment is allowed, investors have to give notice long before withdrawal.

Furthermore, hedge funds are known for their long settlement periods (Moix & Bacmann, 2003:2).[5] Such requirements are usually the result of the illiquid strategies that some funds follow.[6] In order to eliminate this problem, Funds of funds have been created to detect the best managers. This hedge fund strategy entails the management of more than one hedge fund to be managed by a single fund (McCrary, 2002:44). The Fund of funds will thus be in the advantageous position of assembling a multitude of highly skilled hedge fund managers under the management of one fund.

Even though skills are essential for extracting profits from market inefficiencies, skills alone are not enough to generate profits. The other important aspect is the degree of regulation to which the investment vehicle is subjected. In order to avoid stringent regulations, many potential 'fund managers' in the U.S. attempt to register their 'funds' as alternative investment schemes rather than investment companies.

Hedge funds are excluded from being defined as investment companies on the basis of one of two exclusions. The first exclusion is available to hedge funds that have 100 or fewer investors. The second exclusion applies to hedge funds that sell their interests to highly sophisticated investors only. To rely on either exclusion, the hedge fund must restrict its offerings so that they meet the requirements for non-public offerings (U.S. Securities and Exchange Commission, 2003:13).

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[5] The settlement period is the time it takes for the hedge fund to finalise the accounts of their investors after the investment period is over.

[6] Please refer to section 2.6 for the major hedge fund strategies.

A relatively liberal regulatory environment gives the manager the opportunity and the flexibility to implement sophisticated strategies. The particular ability of hedge funds to go short is linked with the possibility of capturing market inefficiencies. Thus it can be said that alternative investments' success can be attributed to the extensive skills and knowledge in the industry together with relaxed regulations (Moix & Bacmann, 2003:2).

Despite the setbacks that the hedge fund industry has suffered in the past, its future appears secure. As the need for increased profits drives investors to enlarge their appetite for risk, hedge funds are becoming the means through which increasingly larger numbers investors attempt to increase their wealth. By 2001, hedge funds worldwide managed approximately $ 500 billion, while mutual funds managed $ 10 trillion. The hedge fund industry has, however, doubled its funds under management and is believed to be managing about $ 1 trillion at present (Anjivel *et al.*, 2001:2).

As the regulatory aspects surrounding the hedge fund industry have been maturing, it is to be expected that more money would be invested in hedge funds worldwide. This increased interest in hedge funds creates a growing need for increased risk management policies.

The risks pertaining to hedge funds are discussed in chapter 3. Before these risks and the risk management pertaining to hedge funds are discussed, a short exposition of some of the most prominent hedge fund strategies is first given.

2.6 An Overview of Some Prominent Hedge Fund Strategies

Since the risk management strategies of hedge funds differ from one strategy to the next, it is essential that an exposition of the most prominent hedge fund strategies is given.

It is often difficult to classify hedge funds because of the diverse nature of their investment strategies. As hedge funds combine multiple investment strategies they can,

therefore, be classified as either mixed strategy hedge funds or as multiple strategy hedge funds. Furthermore, the nature of their investment strategies can change over time.

Given the above characteristics of hedge funds; major data providers such as, MAR-Zürich, (Managed Account Review), Van Hedge, CSFB/Tremont and Hennessey do not necessarily assign the same investment strategies to the same investment categories. It is thus possible that one data provider may categorise a particular hedge fund as an Equity Market Neutral hedge fund, while another data provider may categorise it as a Market Neutral hedge fund. In many cases, however, the data providers do categorise hedge funds similarly (McCrary, 2002:33).

The following exposition of hedge fund categories might thus differ from that of other existing hedge fund strategies.

2.6.1 Event Driven

These hedge funds endeavour to profit from the adverse circumstances within some companies, and they usually include investment strategies that involve the acquisition, merger, divestment, bankrupting, liquidation and restructuring of companies (McCrary, 2002:37). In order for the hedge fund to profit from such interventions, thorough initial investigation is imperative. Furthermore, intervention must be quick and precise to maximise profits. Through buying and/or selling shares in struggling or distressed firms, the share price of that firm can be manipulated, thereby creating the opportunity to profit from these price movements. Two of these event driven strategies will be discussed in more detail below.

2.6.1.1 Risk Arbitrage or Merger Arbitrage

Despite any suggestion by the name of the strategy, risk arbitrage is not arbitrage. Risk arbitrage or merger arbitrage hedge funds aim to profit from trades that involve a change of corporate governance. The most common strategy involves the buying of

stock in a company shortly after an announced takeover. The hedge fund will acquire stock in a company after its takeover has been announced. Thereafter, the hedge fund will sell short the acquirer's shares. After the completion of the takeover, the long shares in the acquired company are exchanged for shares in the acquiring company. These shares are then used to satisfy the short position in the issuing company. It is possible for the hedge funds to unwind positions early, if prices of the company's shares reflect most of the profit potential (McCrary, 2002:36).

The success of a particular trade hinges almost entirely on whether the announced takeover is completed or not. Such a risk is difficult to hedge: the traders involved must weigh the probability that the deal will be completed and the trade profitable, against the probability of the non-realisation of the deal. In a case where the takeover is unsuccessful, the hedge fund could lose vast amounts of money. The inherent risk is therefore that the deal is not realised (Owens, 2003:4 and AIMA, 2004:9).

2.6.1.2 Distressed Securities

The distressed securities strategy is based on the acquisition of stock or bonds in companies that are in or nearing bankruptcy (Hennessee Group LLC, 2005b). These securities range from low risk (senior secured debt) to high risk (common stock) (Barra Rogerscasey, 2001:11).

Because these companies are struggling financially, their stock is usually bought at a large discount from face value. Buying such securities poses an obvious risk of loss. The distressed securities hedge fund manager should, however, be able to discern between those companies that still possess a fair amount of profit potential, and those that are beyond saving. The reasoning behind the acquisition of distressed securities is that their prices are low (and therefore possible future returns are high) because most investors cannot or will not invest in distressed securities.

Hedge funds that engage in the acquisition of distressed securities are exposed to the risk of default, which is usually not hedged. The main source of this risk is the

liquidation of a financially distressed company, or the incorrect assessment of information regarding the company's finances and potential for improved profitability (SA Hedge Fund, 2003:3). Most of these hedge funds contain unhedged fixed-income securities, and therefore benefit from declining benchmark rates and likewise, suffer from rising rates. As a result, these hedge funds perform poorly when credit spreads (the difference between lending and investment rates) widen, and perform well when credit spreads narrow.

Distressed security investments are illiquid and these hedge funds generally end up owning the securities for years. Consequently, the strategy is susceptible to liquidity pressures should the investment style move out of favour with investors. Hence, these hedge funds usually require longer commitments (increased lock-up periods) from investors.

Despite these longer investor commitments and apparent liquidity pressures these hedge funds have been following a low-risk strategy approach. The performance of distressed securities hedge funds has been moderately high, which is atypical of a low-risk strategy approach. The volatility of their returns is estimated to be almost half that of stock market returns. These hedge funds tend to carry illiquid instruments at cost, or below cost value. Volatility might thus be understated in some instances (McCrary, 2002:41).

2.6.2 Market Neutral

In the market neutral approach, the hedge fund manager will attempt to neutralise market risk by taking opposite positions in the market. In order to achieve this, hedge fund managers hedge securities that are correlated to the market. Because it is difficult for a hedge fund manager to make a profit on a large diversified portfolio, his ability in choosing the right stocks is crucial (Owens, 2003:1).

The four main types of market neutral strategies are discussed briefly below.

2.6.2.1 Long /Short Equity

Managers of long/short equity hedge funds are generally not market neutral. Instead, the hedge fund can be long or short and will change from long to short on occasion. In long/short equity hedge funds, the manager goes long by buying equities at low prices and selling them at higher prices. The hedge fund manager will also go short by selling equities when their price is high, and then buying them back when prices have declined (McCrary, 2002:34). Once both exposures are combined, the manager will have a net exposure on his portfolio. This exposure can be either net long or net short. Long/short equity hedge funds can be long-biased (net exposure is long), short biased (net exposure is short) or have a zero net exposure.

Net exposure to market risk is reduced by having an equal distribution of long and short exposures; thus resulting in a net exposure of zero. The risks in this strategy arise from the stock specific risks of the long and short positions. These hedge funds usually have substantial exposure to specific sectors, and even individual companies. While some long/short equity hedge funds direct most of their efforts towards buying and selling the right stocks (or stock sectors), other long/short equity hedge funds place more focus on market direction. This approach involves shifts from market long to market short on a regular basis. More typically, a manager will overlay a market exposure on an ongoing stock selection program.

Hedge funds that are primarily long or short may be categorized as long/short equity by one data provider, and differently by other data providers. Long/short equity hedge funds represent a large amount of hedge fund types, with up to a third of all money invested in hedge funds invested in them.

2.6.2.2 Equity Arbitrage

The equity arbitrage hedge fund manager will typically buy a basket of stocks and hedge his position by selling short a stock index futures contract, or vice versa. In theory, the hedge fund will buy the appropriate amount of every stock in the

basket/index which can be hedged by a single futures contract. The hedge fund manager may also make use of some combination of futures contracts and then make use of positions in individual issues to fine-tune the relationship.

The equity arbitrage strategy generates moderate returns with moderate risks. Equity arbitrage hedge fund investors are also known to invest in fixed-income arbitrage or convertible bond arbitrage hedge funds. Although both fixed-income and convertible bond arbitrage hedge funds produce greater returns, these returns are also more volatile. In comparison this sector does, however, still maintain substantially less risk than broad market averages (McCrary, 2002:34).

2.6.2.3 Convertible Bonds

Convertible bonds hedge funds are known to be one of the lowest risk and more conservative hedge fund strategies. The hedge fund manager is typically long convertible bonds or convertible preferred stocks that have equity, debt and options characteristics. Convertible securities of a specific company will be acquired while the underlying equities in the same company will be sold, to generate profits from the mis-pricing in the relationship between the convertible bond and the equities (Owens, 2003:2 and Bailey *et al.*, 2004:23). These hedge funds combine hedges in the underlying common stock; nonconvertible debt; options on the common stock; and futures and options on broad equity indices (McCrary, 2002:38).

Convertible bond arbitrage hedge funds generally have a very low correlation with aggregate stock and bond returns. They are sensitive to credit spreads; benefiting from narrow credit spreads and declining default risk, and suffering when spreads widen. Convertible bond arbitrage hedge funds can carry leverage positions of up to 10:1, are vulnerable to declines in option volatility (some hedge funds more so than others) and generally profit from higher volatility (McCrary, 2002:39).

2.6.2.4 Fixed Income Arbitrage

The fixed-income arbitrage hedge fund presents the investor with a very low risk investment option. The downside of such low risk is, however, evident in the low returns that these hedge funds offer. Fixed-income arbitrage is comprised of trades between the cash and futures markets, between yield curve strategies, between credit and default strategies and between synthetic money market instruments using foreign issues and forward currency exchange rates (Bailey *et al.*, 2004:24).

Because the more established markets have become increasingly efficient, arbitrage opportunities have declined drastically. To overcome the low profit percentage on each individual trade, these hedge funds make use of exceptionally high leverage positions. Many of these hedge funds are known to 'buy the curve' (buy shorter maturities and sell short longer maturities), or 'sell the curve' (sell short the shorter maturities and buy longer maturities), hoping to profit from changes in return spreads between the sectors (McCrary, 2002:39).

2.6.3 Long Only Leveraged

Unlike the long/short hedge fund discussed above, long only hedge funds do not engage in the short selling of equities, nor do they hedge to minimise inherent market risk. These hedge funds also differ from the traditional equity hedge funds, in that they take on leverage to increase returns (MarHedge, 2001:2). Long only leveraged hedge funds are usually found to operate in emerging markets, because of their restrictions on short sales. The hedge fund manager is thus given the authority to use leverage and collect incentive fees.

2.6.4 Short Sellers

The hedge fund managers following this approach are bearish and take the position that stock prices will fall (Hennessee Group LLC, 2005b). Accordingly, the hedge fund manager will borrow stock and sell it, expecting to buy the same stock back after the

price has dropped. As only overvalued securities are shorted, this strategy is sometimes also called 'short bias' (AIMA, 2002:14).

Short sellers should not be confused with short bias long/short hedge funds. Although short sellers are sometimes characterised as a subset of long/short hedge funds, short sellers are only allowed to sell securities short. However, short bias long/short hedge funds may also go long in securities (MarHedge, 2001:2).

2.6.5 Futures Funds

These hedge funds are active in listed financial and commodity future markets, as well as global currency markets, and seek profits from directional moves in the positions they hold (long and short). This strategy is based firmly on speculation with regard to the direction of market prices. While some futures hedge funds focus on a single asset class, such as currency or fixed income, others use a variety of instruments. Hedge funds that use a variety of instruments are less likely to be correlated with stock and bond returns. The hedge fund manager will often attempt to develop a consistent trading strategy applicable to most of the actively traded futures contracts (McCrary, 2002:43).

The traders trading in the commodities and currency markets make use of three major analytical techniques: technical, fundamental and relational analysis (Du Toit, 2003:98). Systematic traders are inclined to make use of price and market specific information (often technical), so as to follow trends while discretionary managers use a less quantitative approach, relying rather on both fundamental and technical analysis (Barra Rogerscasey, 2001:13). Futures hedge funds tend to perform better when volatility is high and perform poorer when markets are quiet.

2.6.6 Mortgage Arbitrage

Although, mortgage arbitrage hedge funds are sometimes characterised as fixed-income arbitrage, they are usually put in their own category. Mortgage arbitrage hedge

fund managers, such as fixed-income arbitrage managers are adversely affected by unfavourable movements in the interest rate. Mortgage-backed bonds are complicated instruments that resemble a bond paired with a short position in an embedded call option.

The instruments traded start out as mortgages and are then pooled into pass-through securities. These securities are then re-engineered into Collateralized Mortgage Obligations (CMOs) and Real Estate Mortgage Investment Conduits (REMICs). Because almost all home owners have the right to pre-pay their loans at face value without penalty, the loan can resemble a call option; and therefore, most mortgage-based securities are callable securities. CMOs and REMICs are specifically designed to divide the risk of these call options (or pre-payment, in the mortgage vernacular) among investors, so as to add value to the collection of instruments (McCrary, 2002:40).

While some securities cause very little option risk, other securities possess magnified option risk. The risk in mortgage-backed bonds varies depending on duration, credit exposure and the degree of leverage (Agarwal & Naik, 1999). The hedge fund manager will first identify undervalued and overvalued issues. The low-risk issues are then priced similarly to other types of low-risk debt securities, and are easy to sell. The high-risk securities, on the other hand, are difficult to sell and are usually attractively priced. Mortgage hedge funds are important owners of these risky issues, which are sometimes called referred to as 'toxic waste'. The mortgage-backed market is primarily U.S. based, and mainly deals in over the counter (OTC) instruments. (Barra Rogerscasey, 2001:13).

2.6.7 Emerging Markets

As is to be expected, emerging markets hedge funds invest in securities of less developed economies. Emerging market hedge funds are not market neutral. These hedge funds are very sensitive to economic and political factors due to the nature of emerging market economies as a group. These emerging market investments have a

tendency to be quite volatile, and thus a variety of economic and political events can significantly influence the prospects for these instruments (Hennessee Group LLC, 2005b).

Adding to this volatility, is the fact that there is not typically an organized lending market for these securities, thus making it difficult to sell short most issues. Most instruments do not have futures contracts that reasonably track these issues. As a result, buyers are generally not able to hedge risk.

Market makers cannot cushion change in demand for the issues by inventorying or selling short issues to investors (Bailey *et al.*, 2004:6). Most hedge funds also track the broad market indices such as, Standard & Poor's 500 index and other world equity indices, more closely than many other hedge fund strategies (McCrary, 2002:41).

2.6.8 Equity Market Neutral Funds

Equity market neutral hedge funds combine issues into similarly behaving long and short portfolios within a particular country. Normally, the manager will attempt to create similar sector exposure, market capitalization, Beta and currency risk in his long and short portfolios. In addition, these portfolios are also not typically comprised of similar securities, but are constructed with high-powered statistical models that allow for similar aggregate behaviour. In their individual state these portfolios will however behave differently.

2.6.9 Global Funds

Although, this approach is closely-related to the global macro hedge fund approach, the global hedge fund can be divided into three categories: international, regional-established and regional-emerging.

2.6.9.1 International

In this approach, the hedge fund manager does not pay attention to economic change in his home country but concentrates on changes that occur in other parts of the world. He will then invest money in countries, based on the amount of risk and possible returns. The hedge fund manager will invest in a particular country, based on the opportunities in that particular country (a bottom-up approach). It is thus possible for a hedge fund manager to have stocks across different markets at any specific time (MarHedge, 2001:1).

2.6.9.2 Regional-Established

When the hedge fund manager focuses on opportunities in established markets he may seek opportunities in the U.S., Europe and Japan: the so-called U.S. opportunity, European opportunity and Japanese opportunity (MarHedge, 2001:1). The money will be shifted between these already developed markets towards the best potential opportunity.

2.6.9.3 Regional-Emerging

When the hedge fund manager focuses on less established markets, he will seek opportunities that render more profitable prospects. These opportunities do, however, pose a higher risk. Hedge fund managers that invest in emerging markets will either be long securities or be active in the cash market (MarHedge, 2001:1). This is common because shorting securities is not permitted in some emerging markets.

Due to the above, regional-emerging hedge fund managers tend to be attracted to specific emerging markets, and will usually invest in countries that are growing at a reasonably fast pace.

2.6.10 Global Macro Funds

The global macro hedge fund manager can invest in stocks, bonds, currencies and commodities, and make investment decisions based on broad economic (especially international) factors, such as interest rates and government policies (Hennessee Group LLC, 2005b and Bailey *et al.*, 2004:24). The hedge fund manager seeks to profit from directional movements in the positions of the abovementioned instruments. Even though the hedge funds may have long and short positions in a range of assets, the positions may not be designed to hedge each other.

Macro hedge funds will invest mainly in liquid, efficient markets and maintain leverage between 6:1 and 10:1. When considering the outright nature of their positions, this ratio is higher than many equity hedge fund strategies (McCrary, 2002:42).

Global macro hedge funds have the reputation of generating some of the highest returns in the industry. They are also among the most volatile strategies, and have had higher correlations with stock and bond returns than most other hedge fund strategies. Despite their significant correlations with stock and bond returns, they are still valuable diversifiers in a conventional stock/bond portfolio. Global macro hedge funds are generally used to increase the overall returns on a conventional portfolio (McCrary, 2002:43).

2.6.11 Fund of Funds

Funds of funds invest in various strategies and asset classes to provide a more stable long-term investment return than any of the individual hedge funds (Hennessee Group LLC, 2005b). Instead of investing directly in securities, funds of funds invest in other hedge funds, and it is not uncommon to find funds of funds that invest in more than 20 managers. There are two types of funds of funds: diversified funds and niche funds. The diversified fund allocates capital to a variety of hedge fund types while the niche fund allocates capital to a specific type of hedge fund (SA Hedge Fund, 2003:3 and Barra Rogerscasey, 2001:11).

Funds of funds offer several advantages over a direct investment in a hedge fund. Due to their size, funds of funds are able to diversify their investments without needing to concern themselves about minimum investment levels. These hedge funds are also in the position to make investments that are not available to individual investors.

As long-term investors with successful hedge funds, funds of funds may have money invested with funds closed to new investment. It is thus in a better position to evaluate new hedge funds, and enter before the hedge funds get too large to be effective (McCrary, 2002:44).

Because many hedge funds have long lock-up periods they might experience illiquid periods. A fund of funds is, however, more likely to be given special permission to exit before lock-up periods have expired and thus has the advantage in this regard. As a result, the lock-ups on individual hedge funds matter less because the number of hedge funds under the fund of funds' control creates sufficient liquidity. There is often no need to liquidate positions when investors withdraw, due to the simultaneous influx of other investors (McCrary, 2002:44).

2.6.12 Conclusion

The exposition detailed above should not be taken as the only valid classification of hedge funds into investment styles, since it varies from data provider to data provider. The reason for this difference in classification stems from the differences in techniques, tactics and the universe of assets found within a particular strategy. Most of the hedge funds in a particular strategy will, however, respond similarly to variables such as interest rates, stock returns, credit spreads and market volatility, regardless of their small differences.

Two types of strategies can be distinguished: directional and non-directional strategies. Hedge fund strategies exhibiting low correlation with the market are classified as non-directional, while those exhibiting high correlation with the market are classified as directional.

Directional strategies are found to have more market exposure, and therefore lower Sharp ratios, than non-directional strategies.[7] Non-directional strategies have higher Sharp ratios and lower downside risk[8] (Agarwal & Naik, 1999). Because of their low market risk, these strategies are good vehicles for other hedge funds, to diversify their current exposure by (Barra Rogerscasey, 2001:13).

Hedge funds, as an investment group are, however, active on exchanges around the globe, participating in daily trading activities. Since all of these strategies require active participation on world markets on a daily basis, they are all susceptible to adverse trading conditions. One such 'condition' is the day-of-the-week effect (discussed in detail in Chapter 3). The following section briefly considers the current status of the hedge fund industry in South Africa.

2.7 The South African Hedge Fund Industry

As in other parts of the world, hedge funds have taken off in South Africa. It is important to note that the risk management of a hedge fund will be influenced by the legislation and dynamics of the market within which it operates. Since the South African hedge fund manager is susceptible to the changes in the local market, a short exposition of the South African hedge fund industry follows.

2.7.1 The Status and Performance of Hedge Funds in South Africa

The South African hedge fund industry is currently estimated at some R 6 billion ($ 1 billion) in assets under management. These assets are managed by more than 50 local hedge funds and 6 funds of hedge funds, as well as a number of offshore funds of funds (Old Mutual, 2005:1)

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[7] The Sharpe ratio is a measure of how well a fund is rewarded for the risk it incurs. A higher Sharp ratio indicates better returns per unit of risk taken. A Sharpe ratio of 1:1 indicates that the rate of return is proportional to the risk assumed in seeking that reward (FTSE, 2005:22).
[8] Downside risk is the risk that the investor will loose money when the market decreases.

The local hedge funds are mostly biased towards long/short strategies which are largely focussed on the equity market. The South African hedge fund market is also comprised of several fixed income hedge funds. The local investment industry is characterised by a reasonably well-developed scrip (stock) lending market. There are, moreover, new prime brokers and custodians with many reputable international players entering the local industry. The local banks are also constantly striving to offer a broad range of OTC derivative instruments to complement the well-established and liquid index futures and options markets (AIMA, 2004:1).

Up until now hedge funds in South Africa have been characterised by a lack of formal regulations (i.e. permitted structures) with which to pool and unitise hedge funds. The launch of the South African Chapter of the Alternative Investment Management Association (AIMA) in October 2003, however, marked a significant point in the development of the fledgling local industry (AIMA, 2004:1).

According to a survey conducted by the University of Pretoria, it appears that there is a keen appetite for hedge funds by pension funds. The survey revealed that 62 percent of the institutions interviewed had no prior exposure to hedge funds, but would consider investing in them were it not for poor regulatory assistance, an appropriate product offering by hedge funds and a lack of knowledge of hedge funds. A large percentage (68 percent) had poor to average knowledge of the industry, and of the 68 percent many relied solely on the financial press for information. Half of the respondents expected lower returns on hedge funds than on other strategies while 20 percent expected hedge fund returns to be higher (AIMA, 2004:2).

The results suggested that hedge funds have become an integral part of the local investment scene and that trustees are increasingly considering hedge funds despite their poor disclosure and apparently non-existent regulation. Professor Hugo Lambrechts of the University of Pretoria's financial management department stated that, "While it appeared from the survey that knowledge about hedge funds was limited, the reasons the respondents gave for investing were reassuring" (AIMA, 2004:3).

The local interest in hedge funds, by high net-worth individuals, continues to grow with investors seeking protection from the volatility South Africa has experienced in the equity and bond markets. This aspect has been particularly worrying as bonds are losing their performance ability in the local market with inflation targets back to the designated range.

South African pension funds are already somewhat familiar with hedge funds as they often form a significant portion of their international assets invested in funds of hedge funds. Coronation invests its entire 15 percent offshore allocation in hedge funds (or alternative investments). Rand Merchant Bank (RMB), Coronation and Old Mutual invest up to 18 percent of their international portfolios in funds of hedge funds (Financial Mail, 2004:1).

Less sophisticated local investors have a somewhat prejudiced view of hedge funds, because of past failures of some high profile international hedge funds. There is also the misconception that hedge funds have a higher risk profile than other investment instruments. The South African hedge fund industry is, however, bound to grow aggressively in the short term with low interest rates, a volatile currency and the potential return of an equity bear market. With the creation of the local AIMA Chapter, the move towards a regulated and transparent industry and the ability to market hedge fund returns not too far off, the South African hedge fund industry is set to soar (AIMA, 2004:3).

The risk management process in a hedge fund is greatly influenced by the regulatory aspects in a market. The regulation of the hedge fund industry thus features significantly and a brief discussion of the regulation of this industry in South Africa follows.

2.7.2 The Regulation of Hedge Funds in South Africa

There are currently no disclosure requirements or investor protection regulations applicable to any funds investing in alternative asset classes in South Africa. As part of

the 'alternative investment' category, hedge funds have long been the exclusive investment vehicle for wealthy individuals. In recent times, other institutional investors have also been attracted to partake in the profits that these investment vehicles provide. Since the average hedge fund now has to cater for a broader investment group, regulations have become increasingly important (Old Mutual, 2005:3)

Hedge funds are not exposed to the same restrictive regulations that other investment vehicles are exposed to, with regard to borrowing and leverage. Hedge funds also allow for the collection of performance fees.[9] Investors are typically only permitted to redeem their interest on their investment periodically, for example, quarterly or semi-annually. Further, hedge funds make ample use of derivatives for speculative purposes and they have the ability to short sell securities.

Because of these high risk investment strategies, hedge funds are prohibited from advertising their services to the public (U.S. Securities and Exchange Commission, 2003:29). This is not just the case for South Africa. The advertising of such services is prohibited all over the world. Many hedge fund managers are thus reliant on their reputations as proficient managers to attract new investors. It is also common for hedge funds to market themselves to sophisticated investors through mediums such as partnerships and trusts (van Royen et al., 2002:1).

The Association of Collective Investments (ACI), the Investment Managers Association of South Africa and AIMA are the key role-players involved in the establishment of regulatory measures in hedge funds. This followed an extensive consultation process in 2004. These regulations are expected to be passed either late in 2005 or early 2006 (Shames, 2005:1).

Even though regulation is desirable from some investors' perspective, the greatest gain for the industry will be achieving tax certainty. The success of regulations will possibly hinge of the view of the fiscus. If the South African Revenue Service (SARS) decides

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[9] These fees are usually around 20 percent on the profit made by the fund manager. They are collected over and above the annual management fee (U.S. Securities and Exchange Commission, 2003:61).

to levy a Capital Gains Tax (CGT) when an investor redeems, then the majority of hedge funds are likely to convert to the regulated structure. If, however, SARS views hedge fund investments as a revenue and chooses to tax gains at income tax rates, hedge funds would probably not convert to the regulated structure.

2.8 Conclusion

Hedge Funds have been around for over five decades and have survived several economic and financial crises. These investment vehicles differ from average (regular) investment vehicles in the sense that they make use of various high risk investment strategies and employ high risk financial instruments to earn higher profits. Hedge funds are further known for their unique investor base. The largest segment of hedge funds' investor base still remains wealthy individuals. However, because hedge funds are well known for their ability to generate high returns for their investors, more institutionalised investors are attracted to hedge funds. These institutionalised investors includes amongst others, pension funds and medical schemes.

Institutionalised investors such as pension funds and medical schemes, has less affluent investors (such as pensioners and people from a middle income sector). It is therefore necessary for these institutionalised investors to invest in investment vehicles with high returns and low risk. In order for hedge funds to maintain and expand their investor base (mainly in the form of institutionalised investors), they should follow a very stringent approach to their risk management process.

This concludes the discussion on the hedge funds, their history and development as well as the current status of these hedge funds in South Africa. The next chapter focuses on risks for hedge funds as investor type, and on the ways these risks are measured and managed. These risks are then discussed with specific reference to the hedge fund industry.

CHAPTER 3

Risk

In a strict sense there isn't any risk – if the world will behave in the future as it did in the past

Merton Miller – LTCM, Nobel Lauréat

(Du Toit, 2002)

3.1 Introduction

Since hedge funds are investors, and all investors are subject to risk, it is important to consider the risk management process within the typical hedge fund. It is, however, not possible to assess the risk management process without prior knowledge of some risk measurement tools. These risk measurement tools include Beta, VAR, Correlation and Volatility and Liquidity risk.

Although all of these risk measurement tools are important for measuring risk within a portfolio, the focus is on volatility and its measurement tools. The reason for this emphasis is that the dissertation progresses towards testing for volatility patterns in the South African All-Share index returns, in order to confirm the possible existence of a day-of-the-week effect in this market. Moreover, the volatility in market returns correlates with liquidity in the market (Guo & Savickas, 2005:25).

This chapter delineates the most prominent risk measurement tools in section 3.2. These tools are used to assess the risks relating to hedge funds. Thereafter, section 3.3 covers a brief discussion revealing the hedge fund management process, in order to further elucidate the risk management facet of hedge funds. This chapter will serve as a preamble to market anomalies, which may pose an additional risk for hedge fund managers to manage, which are discussed in chapter 4.

3.2 Risk Measurement

In order to discuss the day-of-the-week effect as an additional risk for the hedge fund manager, it is imperative that an exposition of the risk management environment is given within the typical hedge fund. However, this first entails a brief analysis of the main risk measurement tools.

This discussion commences with Beta, and is then followed by VAR. These two risk measurement tools are typically used to measure the risk of a fund's portfolio. Thereafter, correlation and volatility, and liquidity risk are discussed. Unlike Beta and VAR, correlation and volatility, and liquidity risk are more focussed on market conditions and trends.

3.2.1 Beta

Beta determines the volatility, or risk, of a fund in comparison to that of its index or benchmark (FTSE, 2005:16).[10] A fund with a Beta very close to 1 indicates that the fund's performance closely matches the index or benchmark. A Beta greater than 1 indicates greater volatility than the overall market volatility, while a Beta less than 1 indicates less volatility than the benchmark (Croome, 2003:2). The greater the Beta value, the more the market or non-diversifiable risk. Beta can be positive or negative: a positive Beta value suggests that both the market's and the asset's return move in the same direction when market conditions change.

The overwhelming majority of assets have a positive Beta. Assets with a negative Beta are important instruments for portfolio diversification, as they allow the creation of a portfolio with a zero Beta, i.e. without systematic risk (IVolatility, 2005). Different measures of correlation and volatility can result in different measures of Beta. Hence, Beta can be represented as a Simple Moving Average (SMA) Beta, an Exponentially Weighted Moving Average (EWMA) Beta or a Generalised Autoregressive Conditional Heteroskedasticity

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[10] It is to be noted that the word *fund* is used as an umbrella term to refer to all types of funds (pension funds, mutual fund, hedge funds etc.).

(GARCH) Beta.[11] Hedge funds are known for investing in illiquid assets in their quest for higher returns. Calculated Beta values must, therefore, be carefully considered if they are to be of any use for hedge funds; since liquidity also plays a role in the determination of Beta values (Botha, 2005:74).

Beta should thus to be considered a solid measure of market exposure, which makes it the ideal tool for assessing the inherent risk profile of the hedge fund's open positions. It is, however, also vital that Beta be used in conjunction with other risk measurement tools in order to ensure the full benefit of its use.

3.2.2 Value at Risk

VAR is a standard measure of risk among financial institutions. The VAR of a financial instrument is a measure of the size of the loss that is expected to occur with a specified frequency (Litterman, 2003:28). Formally, a VAR measures the worst expected loss over a given period under normal market conditions, at a given confidence level (Benninga & Wiener, 1998:1). That is to say, that VAR is the lowest quantile of the potential losses that can occur within a given portfolio during a specified time period.

The VAR measurement tool is considered to be one of the most important risk measurement tools in the industry (Litterman, 2003:28). It was set in motion by J.P. Morgan in 1993 and is considered to be the first step towards a more efficient risk control and management system by all fund managers, investors and academics (Yan, 2000:1).

According to the J.P. Morgan Technical Report (1994) there are two approaches in calculating a VAR value: the simple approach and the delta-gamma approach. In the simple approach, the VAR is positively related to the standard deviation of the portfolio (Yan, 2000:1). The underlying assumption of the simple approach is that the returns of the underlying assets follow a normal distribution. If the normality assumption is violated it is not appropriate to use the simple approach. In such a case it is advisable to

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[11] More is said about SMA, EWMA and GARCH models in section 3.2.3.

rather make use of the delta-gamma approach, which allows for the matching of the moments of the underlying asset's return with certain distribution. This distribution is then used to estimate the VARs (Yan, 2000:1).

As the VAR concept evolved, so too did the various approaches with which VAR is calculated. An exposition of three recent approaches is given below. These approaches include the Historical method, the Variance Covariance method and the Monte Carlo simulation method.[12] A brief discussion of these methods is provided below.

3.2.2.1 Historical Approach

This approach assumes that the change in the market conditions from today to tomorrow be the same as the changes that took place some time in the past. The historical approach is based on actual results and if, during this period, major market events takes place these results would be accurately assigned by the historical method (Benninga & Wiener, 1998:4).

The historical approach is not complex to use and historical simulation is easy to implement. This approach is also not dependent on assumptions regarding the return distributions. Since the historical approach makes use of actual historical returns over time there is no need for assumptions regarding the normal distribution of returns.

For this reason, this method is equipped to accommodate fat tails in the distribution of return data (Dowd, 1998:133). A further advantage of this approach is that there is no need to estimate correlations and volatilities, hence eliminating the risk of miscalculating these measures. Lastly, the historical approach takes other important statistical measures into account.

There are, however, also some specific negative aspects concerning the historical approach. One drawback particular to the historical approach is that it is entirely

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[12] The mathematical exposition of these methods goes beyond the scope of this dissertation. More information on the calculation of these methods can be found in Benninga and Wiener (1998) and Botha (2005).

dependant on historical results of the specific historical data set, and that it is not especially useful for scenario analysis (Benninga & Wiener, 1998:4). The assumption that the past will repeat itself can thus lead to some distortions in VAR in a number of circumstances.

Another drawback is that the historical approach has difficulties in explaining a changing portfolio mix over time, and may produce a VAR that does not reflect the current situation. A third drawback is that the historical approach requires a large amount of data points for the model to construct a reasonable VAR value (KPMG Risk, 1997:44).

3.2.2.2 Variance Covariance Approach

This method is based on the assumption that the short-term changes in the market parameters and in the value of the portfolio are normal. Furthermore, the Variance Covariance approach reflects the fact that the market parameters are not independent. It is, however, restricted to the first degree of dependence-correlation (Benninga & Wiener, 1998:5). An equation for the Variance Covariance approach can be given by (Payant, 1996):

$$VaR = N \times \sigma \times Cl \times \sqrt{T}, \qquad (3.1)$$

where

N is the position size (number of times),

σ is the potential volatility of market factors (correlation of observed probability distributions of market factors),

Cl represents the confidence level of volatility estimation (number of standard deviations of probability distribution),

T is the holding period horizon extrapolation (square root of number of days).

VAR is comprised of a multiple portfolio of standard deviations (a linear function of individual covariances and volatilities). For this reason, portfolio VAR is calculated by

employing the variance covariance matrix and information on the size of the individual positions, in order to determine the portfolio standard deviations.

In most cases, historical data is used to build the variance covariance matrix for the market factors, making this aspect of the calculation dependent upon the time period selected. The overall VAR measurement can be calculated by multiplying the standard deviation by a confidence interval parameter and a scale variable that reflects the size of the portfolio (KPMG Risk, 1997:123).

The major advantages of using the variance covariance approach are that it is perspicuous, has a simple equation and is a smooth, well behaved continuous function. Furthermore, much more information is conveyed by this method, and it is also ideal for linear positions in normal risk factors (Botha, 2005: 83).

On the downside, the variance covariance approach is not suitable for the handling of non-linearity. The variance covariance approach is based on the assumption that the underlying market factors have a multivariate normal distribution, although there is evidence that returns are not normal, thus entailing leptokurtosis and fat tails (Linsmeier & Pearson, 1996:10). The variance covariance approach can be very misleading if returns are not normal. Like the historical approach, the variance covariance approach also has problems with extreme events in the absence of the application of the extreme value theory (Botha, 2005:87).

3.2.2.3 Monte Carlo Approach

The Monte Carlo simulation methodology has a number of similarities to historical simulation. However, they differ in that, rather than carrying out the simulation using the observed changes in the market factors over the last N periods to generate N hypothetical portfolio profits or losses, choice of a statistical distribution that is believed to adequately approximate the possible changes in the market factors is made (Linsmeier & Pearson 1996:15).

This method is based on the assumption that some information about the joint distribution of market changes is available. By making use of this distribution, a large number of scenarios can be randomly drawn and the portfolios can be priced for each scenario. A rich set of scenarios gives a good approximation of the distribution of the final values of the portfolio.

The lowest q-quantile of this distribution can be used as an approximation to VAR. Moreover, this method allows for a dynamic improvement: one can run a small set of simulations, get a preliminary result and then improve it by running additional simulations, if necessary (Benninga & Wiener, 1998:6). The VAR is then determined from this distribution.

3.2.2.4 Conclusion

The question remains; which of the three approaches will render the best method of calculating VAR. The answer, however, does not depend on the accuracy of the approaches themselves. They differ in their ease of implementation, ease of explanation to senior management, flexibility in analyzing the effect of changes in the assumptions, reliability of their results and their ability to capture the risks of options and option-like instruments. The best choice is thus to be determined by the risk manager himself based on which of these aspects he considers to be the most important.

3.2.3 Correlation and Volatility

Accurate measures and reliable forecasts of volatility are crucial for derivative pricing techniques, as well as trading and hedging strategies that arise in portfolio allocation problems. Correlation and volatility are known to be the most generally used measures of determining risk in finance. They are also used to calculate Beta. Volatility is of specific importance for the establishment of a day-of-the-week effect, and is discussed in more detail in subsequent sections.

3.2.3.1 Correlation

The correlation between two variables reflects the degree to which the variables relate to one another (Luke, 2005:1). Pearson's product-moment correlation coefficient (r), also referred to as the sample correlation coefficient, is the most common measure of correlation. This correlation coefficient is a measure of the extent to which two samples are linearly related (Luke, 2005:1). Pearson's correlation can assume any value between -1 and $+1$, depending upon the degree of the relationship. This is illustrated in figure 3.1 below.

FIGURE 3.1   CORRELATION GRAPH
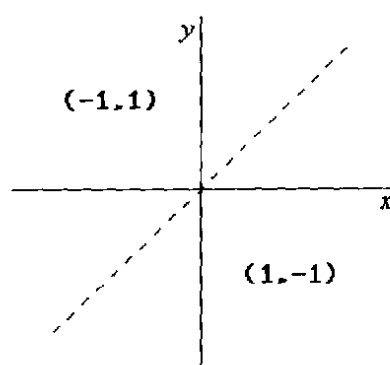
(Luke, 2005:1)

The values -1 and $+1$ indicate perfect positive and negative relationships respectively. A value of zero indicates that the variables do not co-vary linearly. The degree of co-movement between return variables is particularly important for risk measurement, hedging and asset allocation. Pearson's correlation is usually given by the formula (Hull, 2000:242):

$$\rho = \sqrt{\frac{1}{T-1} \sum_{r-1}^{T} (x_t - \bar{x}) \cdot (y_t - \bar{y})}, \qquad (3.2)$$

where

ρ is Pearson's correlation,

T represents the entire observation period,

x_t and y_t are the two different return variables, generated from two price series.

3.2.3.2 Volatility

The dispersion of the rates of return around the average rate of return is frequently used to measure the risk of the investment. In the case where the rate of return deviates far from the average, it means that the dispersion or standard deviation is large and there is a relatively large volatility (risk) with such an investment (Levy, 2002:133). Volatility can be measured in a variety of ways: SMA, EWMA and GARCH (Sin & Lam, 2004:16).

A SMA is simply the average of a set of variables (such as stock prices) within a specific time period. The average is 'moving' with the passing of time and helps to smooth the data from any spikes (GIFT, 2005:3). This is achieved by using the new data point and simultaneously discarding the oldest data point.

To determine the t-period SMA volatility (or standard deviation) the t-period average of price returns has to be determined first. Thereafter the sum of the squares of the differences between each period's return and that of the average is then determined, and then measured over the full k-period. The quotient of this sum and $k - 1$ is calculated and the overall square root determined for statistical reasons.

This model is the most widely used volatility model in VAR studies and is given by (KPMG Risk, 1997:153):

$$h_t = \sqrt{\frac{1}{k-1} \sum_{s=t-k}^{t-1} (x_s - \mu)^2} \,, \tag{3.3}$$

where

h_t is the Simple Moving Average volatility measure,

k is the number of observations,

x_s is the observation at time index t,

μ is the expected value of all observations.

This means of determining risk accounts for the increase or decrease in the price but does not, however, manifest itself quantitatively in the SMA. Thus the time order of the data (observations) is not accounted for when using the SMA calculation in order to calculate volatility. Another drawback is the fact that in using SMAs use is made of an equally weighted average. This is not ideal for the simple reason that recent data is far more important for volatility forecasting.

This problem can be addressed by introducing exponentially weighted moving averages as a measurement tools for volatility. By making use of the EWMA method, the more recent data is given a larger weighting. The EWMA model assigns the most weight to the previous day's value, which in turn is dependant on the day before and so on (Pafka & Kondor, 2001:3, also Goodworth & Jones, 2004:5). This model is thus superior to the SMA model in that it is able to capture the more recent and therefore more important data for calculating volatility.

The EWMA model depends on the parameter λ (where $0 < \lambda < 1$), referred to as the decay factor. This decay factor captures a fraction of the previous day's value and defines a relative weight $(1 - \lambda)$ that is applied to the most recent volatility and a weight of λ to the most recent price return. The parameter also defines the effective amount of data used in estimating the volatility. A value closer to 1 indicates that most recent observation has a smaller impact on current volatility, while a value closer to 0 indicates that the most recent data has a larger impact on current volatility.

The formula of the EWMA model can be given by (KPMG Risk, 1997:153):

$$h_t = \sqrt{(1-\lambda) \sum_{s=t-k}^{t-1} \lambda^{t-s-1}(x_s - \mu)^2} \,, \tag{3.4}$$

where

h_t is the tth period volatility;

λ is the decay factor,

$(x_s - \mu)^2$ is the $(t - 1)^{th}$ period squared return.

There is also a third model available for calculating the correlation and volatility of a portfolio, namely GARCH, which is a specialised form of the ARCH model. The ARCH model developed by Engle (1982) permits the variances of the forecasted return terms to change with the squared lag values of the previous error terms. This is known as an (ARCH (q)) and can be expressed by (Nelson, 1991:348):

$$\sigma_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \ .$$ (3.5)

Not long after the publication of the ARCH paper, Engle's graduate student Tim Bollerslev introduced a model that expanded the ARCH and called it the generalized ARCH (GARCH) model. This model takes the following form (Kungl. Vetenskapsakandemien, 2003:15)[13]:

$$\sigma^2_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \ .$$ (3.6)

The first-order ($p = q = 1$) GARCH model has since become the most popular ARCH model in use. Compared to Engle's basic ARCH model, the GARCH model is a useful technical innovation that allows a parsimonious specification; a first-order GARCH model contains only three parameters.[14]

GARCH is a mechanism that includes past variances in the explanation of future variances, thus allowing the user to model the serial dependence of volatility. GARCH models are thus superior to SMA models as they employ the assumption that more recent events are more relevant and therefore should have higher weights. The model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero.

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[13] It is to be noted that both the standard ARCH and GARCH models above have been adapted from the original texts in order to promote uniformity.

[14] This specification requires that $\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j < 1$, in order to satisfy the non-explosiveness of the conditional variances. Furthermore, each of α_0, α_j and β_j has to be positive in order to satisfy the non-negativity of conditional variances for each given time t.

The most widely used GARCH specification asserts that the best predictor of the variance in the next period is a weighted average of the long-run average variance, the variance predicted for this period; and the new information, that is captured by the most recent squared residual in this period (Engle, 2001:4).

GARCH is thus considered a time-varying volatility measurement model that captures the effect of changing volatility over time. Financial return volatility data is influenced by time-dependent information flows which result in pronounced temporal volatility clustering. These time-series can be parameterised using GARCH models. GARCH also takes into account excess kurtosis or 'fat tail behaviour'[15] (Hamao *et al.*, 1990:286). Although GARCH is specifically designed to model time-varying conditional variances, these models often fail to capture highly irregular events.

Both correlation and volatility are important measurement tools in the finance world. These measures together with GARCH are thus used in chapter 4 to detail and explain the day-of-the-week effect of volatility in South African All-Share index returns data.

3.2.4 Liquidity Risk

Liquidity is defined as the ability to convert assets into cash at the prevailing market price (Levy, 2002:18). Liquidity risk is thus the risk that one is not able to covert assets into cash at the prevailing market price, at that particular point in time. This risk is synonymous with both the cost of liquidation and the time to liquidate the position. The risk of the lack of liquidity depends on several factors, such as the number of outstanding shares (Levy, 2002:18). Some assets such as highly-traded bank stocks for example, are inherently more liquid than others.

There are several factors that influence liquidity and therefore, liquidity risk. A prominent factor is position size, which plays a major role due to the fact that the number of shares that an investor can unwind in one day is relative to the day's trading

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[15] The distributions of many stocks or indices have fat tails and therefore deviate from the normal distribution.

volume. The larger the position size relative to the market size, the more difficult it will be to liquidate such a position (Yung, 1999:5). It follows, that it becomes increasingly difficult to unwind positions if there is not a large active market in the specific stock/share (Hirt & Block, 1990:50).

The larger the position size relative to the market size, the more difficult it is to liquidate. Under stress situations where markets become volatile, liquidity also falls significantly as investors often become more risk adverse. In such a scenario, the bank might be forced to keep its position open for a longer period, which will increase its liquidity risk (Yung, 1999:5). Liquidity risk can be divided into exogenous and endogenous liquidity risk (Botha, 2005:98).

3.2.4.1 Exogenous Liquidity Risk

Exogenous liquidity risk originates externally i.e. market characteristics (Bangia *et al.*, 1998:2). It follows then that this risk cannot be caused by any market participant, but has its origin in an external market shock. The market participants will, however, react to this shock by closing out some of their positions in the market, in order to find a safer haven for their investments. This reaction of market participants will then result in a loss of liquidity. This external liquidity shortage will also impact negatively on leveraged positions.

The Russian financial crises of 1998 caused such a liquidity shortage in the market. Russia's devaluation of the ruble caused the Long Term Capital Management (LTCM) fund to suffer approximately $ 1.8 billion in losses in August 1998 (Edwards, 1999:199). At that time, LTCM's simple balance sheet leverage ratio had reportedly climbed to in excess of 25 to 1, and the hedge fund had difficulty meeting its margin call requirements (U.S. Securities and Exchange Commission, 2003:133).

In general, hedge fund managers are comfortable with current liquidity levels in the markets and do not find it excessively difficult to execute trades without having a significant market impact. Many hedge fund managers are cautiously watching

slippage; the difference between the prevailing price at the time of a decision to trade and the realised trade price. If hedge fund managers are involved in similar strategies, and choose to exit their positions simultaneously in the market, this liquidity will fade very quickly. Hedge funds are also inclined to move into more complex assets (where market liquidity is low) in search of higher yields (Sidani & Soueissy, 2003:39). Liquidity in markets where complex assets are traded may, however, not be as great as that found in more traditional markets.

It is clear that any liquidity crisis could be intensified by any event that forces hedge funds to withdraw from the market. Any leveraged hedge fund faces the risk of increasing finance costs/margin payments or cutting their credit line. Typical leverage varies significantly, according to the strategy of the hedge fund. As previously mentioned, leverage may increase rapidly as the markets start to pick up and volatility starts increasing.

There is a wide variety of interpretations of the term leverage. Consequently, a wide variety of methodologies are used for the measurement of the leverage used in hedge funds. These definitions and methodologies fall into two broad categories: economic (debt) leverage and financial (instrument) leverage (FSA, 2005:30). The former refers to leverage generated by increasing assets under management, and therefore investment capacity through borrowings. The latter is generated by making investments on margin i.e. where the cost of an investment is less than the exposure it generates (FSA, 2005:30).

The risk inherent in economic leverage may be multiplied according to the nature of the exposure bought. For example, $ 100 million of economic leverage does not generate the same degree of risk if it is used to purchase a three-year UK government bond as when it is used to purchase a 30-year emerging market bond.

The potential to capitalise on leverage may be growing as prime brokers introduce cross margining. Cross margining is an offsetting position where market participants are able to transfer excess margin from one account to another account whose margin is

under the required maintenance margin. If cross margining is based on negative correlations between positions or strategies that might erode in a crisis scenario, there may be a risk inherent in such activity that is not being recognised (FSA, 2005:31). The source of a hedge fund's leverage could also affect its risk profile. If the hedge fund relies too heavily on a single broker, the hedge fund could be particularly exposed to the risk of leverage being withdrawn. In cases where the source of the leverage has similar market exposures to that of the hedge fund, this risk will be particularly severe.

3.2.4.2 Endogenous Liquidity Risk

Endogenous liquidity is market participant specific (Bangia *et al.*, 1998:2). This liquidity risk sprouts from the specific positions that the particular participant occupies in the market. The participant's liquidity position is thus of his own doing, and is mainly the result of the size of his position. The smaller the size of his position, the more liquid that position will be. In cases where the market order to transact is smaller than the volume available in the market at the specific quote, the order will transact at the quote. The market impact cost will then be half of the bid-ask spread. If, on the other hand, the size of the order should exceed the quote depth; the cost of the market impact will be higher than the half-spread (Subramanian & Jarrow, 1997:170 and Subramanian & Jarrow, 2001:447).

Even though hedge fund managers are running market risk based upon economic and financial leverage, their potential market impact is also strongly linked to the liquidity mismatch between their investments and their investors. If their investors claim their investments after the lock-up period, it may make the hedge fund a forced seller. In some hedge funds, investors can 'buy' managed accounts and side letters that grant enhanced investor liquidity. Smaller and less powerful investors who do not benefit from enhanced liquidity options may find, that by the time their shares are redeemed, prices have moved against them as other investors have been able to liquidate their positions more quickly. This scenario does, however, also impact negatively on the hedge fund in that it might be forced to liquidate more positions in a shorter time-frame to comply with the increase in investor's liquidity needs (FSA, 2005:31).

These liquidity risks may be growing as hedge funds become increasingly reliant upon institutional investors. Although hedge fund managers would prefer to avoid the extra cost associated with managed accounts and side letters, they will tolerate it to secure large scale investments.

3.2.4.3 Theory behind the Modelling of Liquidity Risk

It is essential that the hedge fund manager know when positions should be liquidated and at what price these positions should be liquidated. The standard VAR model implies that there is no liquidity during the holding period of an instrument, and infinite liquidity on the last day of the holding period. When market volatility increases, the model does not account for the fact that liquidity often decreases and the holding period lengthens (Yung, 1999:5).

Measuring liquidity risk is a dynamic concept, when modelling liquidity risk, the model should not only allow for current liquidity but for future liquidity as well. It is often difficult to model wide bid-offer spreads and large price movements directly in a mark-to-future model. Mark-to-future can be defined as the mark-to-market value plus the true forward profit and loss under each and every scenario (Yung, 1999:6). When an investor wants to measure the potential changes in his portfolio, he requires a framework that integrates market and liquidity risks. It is necessary to have a framework that allows one to develop a number of forward-looking scenarios that will accommodate an array of opinions about the future. This framework should also be able to handle a multitude of risks.

Because the VAR at the end of the liquidation period includes both the market and the liquidity risks, the liquidity risk must be isolated from the market risk in a portfolio VAR. This can be achieved by comparing the portfolio VAR with the standard VAR (a methodology where instantaneous liquidation is assumed).

In general, as market volatility increases, liquidity dries up (FSA, 2005:31). The longer it takes for the investor to liquidate his position, the greater the VAR will be. In order

to determine the cost of liquidity, and the time it takes to liquidate the position, liquidation strategies are needed. The four basic strategies are: Instantaneous Liquidation; Unconditional Liquidation; Conditional Liquidation and Scenario Conditional Liquidation.

TABLE 3.1   LIQUIDATION STRATEGIES

	Simulation Category	Scenario	Liquidation Strategy
Infinite Liquidity	Market risk only No impact on liquidity risk	Market risk scenario	Instantaneous Liquidation
Average Liquidity	Market risk with reasonable Amount of liquidity in the market	Market risk scenario	Unconditional Liquidation
Limited Liquidity	Market risk with reduced liquidity, simulating the impact of liquidity under volatile markets	Market risk scenario and High volatility scenario	Conditional Liquidation
Negligible Liquidity	Market risk under the worst case liquidity scenarios, simulating the impact of liquidity under extreme conditions	Market risk scenario and low trading volume scenario	Scenario conditional Liquidation

Adapted from (Yung, 1999)

Under the instantaneous liquidation strategy, it is assumed that infinite liquidity exists and that the position is liquidated at the quoted market price in one day. The unconditional liquidation strategy revolves around the principle that a specific percentage of the portfolio will be liquidated over a fixed period. The liquidation strategy involves the liquidation of the portfolio will be done at the quoted market price. The liquidation of the portfolio will be done at a fixed percentage of the day's trading volume. Finally, the scenario conditional liquidation strategy will involve the liquidation of the portfolio based on the specific scenario that presently manifests itself.

3.2.4.4 Conclusion: Liquidity Risk

Overall, liquidity risk in hedge funds appear to be moderate and increasing, with a potential mismatch developing between the increasingly illiquid investments made by the hedge fund and the increasing liquidity offered to hedge fund investors. Tracking liquidity provision by prime brokers (counter parties) captures just one part of a larger liquidity picture.

Another part of this bigger liquidity picture is discussed in chapter 4 under market anomalies. Low trading volume is generally accompanied by high volatility (Foster & Viswanathan, 1990). It is to be noted that market anomalies (the day-of-the-week effect) fall under exogenous liquidity risk, since they are not under the control of any one market participant. This is a liquidity condition that is created by the cyclical behaviour of all the market participants in a particular market. Further note that each market's liquidity patterns will differ from the next. This difference can be ascribed to various market specific factors, such as country-specific market liquidity, the instruments traded on these various markets etc.

3.3 Risk and Risk Management in Hedge Funds

Since markets will not behave in the future as they did in the past, risk is inevitable. Hedge funds share various risks common to most financial markets investment vehicles, such as market risk, liquidity risk, sector risk and operational risk.

The risks that are associated with hedge funds may generally be divided into three broad areas of concern: portfolio risks, the effect of leverage on portfolio risks and operational risks. Portfolio risks may be further divided into market risk, liquidity risk and credit risk (U.S. Securities and Exchange Commission, 2003:66).

Unlike mutual funds that typically invest in traditional equities and bonds, hedge funds invest in a much wider array of instruments and therefore are exposed to additional sources of risks than those considered in typical asset pricing models (Bailey et al.,

2004:6). It follows therefore that hedge funds have broader mandates than traditional funds, which give managers more flexibility to shift their strategy. The risks inherent in a hedge fund portfolio are a function of leverage, market volatility, diversification, and products and markets traded (L'habitant, 2001:19).

Hedge fund managers are expected to attain performance returns for investors, by making use of strategies that are designed to assume or remove calculated risks, consistent with the hedge fund's investment objective. It is therefore imperative for the hedge fund manager to have an effective risk management system in place.

Risk management is normally a monitoring function that quantifies and tracks the risks involved once investments have been acquired. Effective risk management systems require hedge fund managers to identify, measure, monitor and manage the various dimensions of risk.

The risk management systems used by hedge funds differ from firm to firm. Larger and more established hedge funds often have an internal risk management structure, making use of their own resources and personnel, whilst smaller less established hedge funds usually outsource their risk management function. Some of the less established hedge fund managers have little or no risk management controls (U.S. Securities and Exchange Commission, 2003:66).

A brief discussion of the hedge fund managing process is now provided so as to allow clear comprehension of the risk management process within hedge funds.

3.3.1 The Hedge Fund Risk Management Process

The hedge fund risk management process is comprised of a series of interlinked steps that shields investors' investments against all types of financial risks. Although each step concerns itself with the main financial risks, this section focuses only on the market risk pertaining to hedge funds. These steps are discussed below and are followed by a schematic illustration of the management process (Botha, 2005:113).

Step 1: The previous day's traded portfolio positions are reported to risk management, in addition to daily profit and loss (P & L) and derivative exposures.

Step 2: The risk management team collects the relevant price data from data providers such as Bloomberg, Reuters and other information vendors.

Step 3: A daily risk report is produced, which includes risk statistics such as Beta, daily VAR, liquidity and other important risk measures. The report is forwarded to both hedge fund and compliance management for analysis.

Step 4: Besides the daily risk management report, the hedge fund manager also receives other detailed market information in the form of data analyst recommendations and individual company, data provider and broker reports. All the data is used in the decision-making process.

Step 5: The compliance department receives the risk report and monitors it for breaches of the mandate.[16] In cases where the mandate has been breached, compliance reports are sent to the legal department, the senior manager and the hedge fund manager.

Step 6: In the case of a breach, senior management will demand an explanation from the hedge fund manager.

Step 7: The hedge fund manager assimilates all the available information, which is then used to assist the traders in their decision making process.

Step 8: After all the necessary information has been collected and the mandate has been taken into consideration, the trades are made. During the trading session new positions might be opened, old positions might be closed or existing positions might be increased or decreased.

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[16] The compliance department will ensure that all transactions are kept to the current risk profile of the fund, and that the risk ratios are not changed outside the directive of the fund.

Step 9: Once the trade order is executed, the new positions are sent to the back office for recording purposes.

Step 10: If the hedge fund manager is still not satisfied with the changes made to the portfolio, risk management will be asked to carry out further investigation. This process will repeat itself until the correct mix of positions is achieved. Upon completion of the process all the trades will be correctly executed and the portfolio will comply with the specifications as set out in the mandate of the hedge fund.

FIGURE 3.2   A SCHEMATIC ILLUSTRATION OF THE HEDGE FUND RISK MANAGEMENT PROCESS

Adapted from Botha (2005:115)

Continuous recursion of this process will occur to ensure that the hedge fund's portfolio complies with the specifications in the mandate at all times. These specifications are based mainly on the desired size of the portfolio, the desired return profile of the hedge fund, the desired risk profile of the hedge fund and the prevailing market conditions. The mandate of the hedge fund might undergo subtle changes over a

period of time. The hedge fund manager should be able to incorporate such changes by means of the process above.

In accordance with the risk management process, the hedge fund manager receives information in the form of daily risk reports that include risk statistics. These include, amongst others, market volatility, daily VAR and liquidity (step 3). In addition to these risk reports, hedge fund managers receive other detailed market information in the form of data analyst recommendations, data provider reports and broker reports (step 4). This information is also received by the compliance department, which reports any breach of mandate.

Under normal circumstances (no mandate breach), the hedge fund manager is not under any pressure to order the execution of trades, to ensure compliance to the mandate. However, in the case of mandate breach, the hedge fund manager will be obliged to correct this breach by altering (rebalancing) his portfolio. The hedge fund manager will typically open new positions, close out some old positions, enlarge some positions and reduce other positions. High volatility conditions might, however, render this rebalancing process risky.

In cases when a cyclical pattern in volatility is present in the market, the hedge fund manager will be informed thereof during steps 2 and 3. Such a volatility pattern, more specifically the day-of-the-week effect, should then be managed by the hedge fund manager with reference to the mandate. If the hedge funds' mandate is breached, it is advisable that portfolio rebalancing be attempted during the most favourable market conditions. Such conditions typically occur when liquidity is high, volatility is low and mean returns on the market are high.

3.4 Conclusion

To ensure that hedge fund managers are in a position to manage their portfolios profitably, they need to be aware of all possible risks. This can be accomplished by

making use of the risk measurement tools discussed above, so that hedge fund managers are able to assess and manage risks effectively.

Chapter 4 explores the possibility of the presence of the day-of-the-week effect in the South African market. The test for day-of-the-week effect is done by applying several volatility measurement tools. This effect poses an additional risk which hedge fund managers may need to consider and manage. The day-of-the-week effect develops from the cyclical patterns (volatility patterns) within market returns and can be classified under exogenous liquidity risk.

CHAPTER 4

Market Anomalies

4.1 Introduction

Market anomalies have been the subject of many a paper over the past few decades. The most common anomalies are *the Weekend effect, the day-of-the-week effect,* and *the January effect* (Berument & Kiymaz, 2001:1).

The literature distinguishes between two types of cyclical effects in the market: the cyclical pattern of mean returns and the cyclical pattern of volatility.[17] A short overview of the history of the most of the studies regarding the day-of-the-week effect in markets around the globe now follows. Thereafter, an in-depth study is done on the most important literature with the intention of deriving the ideal model for testing this effect in South African data. It is to be noted that the final model is compiled both from the literature and statistical tests.

4.2 The-Day-of-the-Week Effect: Brief Historical Overview

The day-of-the-week effect was first observed and documented by M.F.M. Osborne, the physicist who applied the concept of Brownian motion to the stock market in 1959 (Osborne, 1959). Since Osborne's discovery in 1959, Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Keim and Stambaugh (1984), and Rogalski (1984) amongst others have confirmed that there are differences in the distributions of stock returns in each of the week days. The results of these studies indicate that the average return on Mondays is considerably less than the average return during the other week days.

Although these studies have been performed on the equity markets in the U.S., the day-of-the-week effect has been investigated for both international equity markets and

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[17] Mean returns are also known as the expected rate of return. The expected rate of return is the average of all the possible rates of return and is sometimes also referred to as the mean (Levy, 2002:153).

international non-equity financial markets. Jaffe and Westerfield (1985a, 1985b) found significant negative mean returns on Mondays in the U.S., Canada and the UK stock markets, and significant negative Tuesday returns in the Japanese and Australian stock markets. Aggarwal and Rivoli (1989) studied the emerging markets of East Asia and observed lower mean returns on Mondays and Tuesdays in the stock returns of Hong Kong, Singapore, Malaysia and the Philippines, from September 1976 to June 1988.

Kato and Schallheim (1985), Chang, Pinegar and Ravichandran (1993), Athanassakos and Robinson (1994), and Dubois (1986) showed that the distributions of stock returns also vary by the week days internationally. The day-of-the-week effect is also detected in the commodity and stock futures markets (Cornell, 1985; Dyl and Maberly, 1986; Gay & Kim, 1987), the Treasury bill market (Flannery & Protopapadakis, 1988), and in the foreign exchange market (Corhay, Fatemi, & Rad, 1995).

While the focus of the above studies has been the seasonal pattern in mean returns, there are several other empirical studies investigating the time-series behaviour of stock prices in terms of volatility by using variations of the GARCH models (French *et al.* (1987), Akgiray (1989), Baillie and DeGennaro (1990), Hamao *et al.* (1990), Nelson (1991), Campbell and Hentschel (1992), and Ogum, Nouyrigat and Beer (2002)). These studies report that the expected returns in stock markets are time-varying and conditionally heteroskedastic.

These studies do not, however, examine the issue of day of the week variations in stock market volatility. French and Roll (1986) point out that the variances for the days following an exchange holiday should be larger than other days. Harvey and Huang (1991) observe higher volatility in the interest rates and foreign exchange futures markets during first trading hours on Thursdays and Fridays.

Studies researching the day-of-the-week effect have been performed with good reason. The existence of predictable seasonal behaviour in stock returns may lead to profitable trading strategies, and in turn, abnormal returns. If a day-of-the-week effect is present within a particular market, investors will be in the position to take advantage of

relatively regular shifts in the market by designing trading strategies, which account for such predictable patterns.

Even though these trading strategies may not be able to generate desired profits, (because of factors such as transaction costs) they may still provide insights for investors. Since the rational financial decision-maker contemplates both the returns and the timing of the investment, the knowledge of a day-of-the-week effect in mean returns will be most helpful in ensuring healthy profits.

Further, should investors be aware of a day-of-the-week effect in volatility patterns, they will be in the position to avoid making key investments on days with high volatility. Since hedge fund managers are responsible for managing their fund's portfolios according to a specific mandate, day-of-the-week patterns are of critical importance to their managers. Simply, if investors can thus identify a certain pattern in volatility, more profitable investment decisions could be made based on both return and risk factors. Ultimately, this would give investors another tool to design profitable strategies.

In order to further investigate the existence of a seasonal effect in the South African financial market, several of the articles mentioned above will be explored in more detail. Section 4.3, the literature study, provides the foundation upon which to base an appropriate statistical model with which the data are modelled for cyclical behaviour.

Thereafter, section 4.4.1 details and explains the data that were used. Section 4.4.2 discusses the model heuristically induced from the literature research, which includes information revealed in the literature study as well as the statistical procedures used in estimating the model. Section 4.4.2.3 describes the first model which is applied to the South Africa data. Chapter 4 concludes with an explanation of the results of all the models fitted.

4.3 Literature Study

In their studies, Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Keim and Stambaugh (1984), and Rogalski (1984) confirm the existence of differences in distributions of stock returns over the days of the week. All of them found that in the U.S., the average stock returns on Mondays is noticeably less than the average returns during the other days of the week.

This literature study explores various articles, in order to derive an appropriate statistical model with which to test for the day-of-the-week effect in the South African All-Share index returns data.

4.3.1 Gibbons and Hess (1981)

In their study, Gibbons and Hess (1981) explore the possibility that expected returns on common stocks and treasury bills on the Standard and Poor (S & P) 500 are not constant across days of the week. They note that the most significant evidence is for Monday's returns, where the mean is usually low or even negative. Despite their findings, they can not satisfactorily explain the occurrence of this effect in the market.

Gibbons and Hess (1981) follow Cross (1973) and French (1980) by applying their model to S & P 500 index data. In addition to this, they test several value and equal-weighted portfolios constructed by the Center for Research in Security Prices (CRSP), for evidence of a day-of-the-week effect. In testing for day-of-the-week effects, Gibbons and Hess make use of several models, the first of which takes the form of a normal OLS model with five dummy variables. The model is given by:

$$\widetilde{R}_{it} = \alpha_{1i}D_{1t} + \alpha_{2i}D_{2t} + \alpha_{3i}D_{3t} + \alpha_{4i}D_{4t} + \alpha_{5i}D_{5t} + \widetilde{\varepsilon}_{it} , \qquad (4.1)$$

where

$\tilde{R}_{it}$ is the returns of index (or security) i in period t, whilst $\tilde{\varepsilon}_{it}$ denotes a stochastic disturbance (error term). D_{1t} is a dummy variable for Monday ($D_{1t} = 1$ if observation t falls on a Monday and 0 otherwise), D_{2t} is the dummy variable for Tuesday, etc. The vector of disturbances, $\tilde{\varepsilon}_{it}$, is assumed to be independently and identically distributed as $N(0,\Sigma)$ where Σ is not assumed to be diagonal. The coefficients $\alpha_{1i};\alpha_{2i};\alpha_{3i};\alpha_{4i}$ and α_{5i} are the mean returns for Monday through Friday.

Their first model does not, however, eliminate autocorrelation caused by the non-trading of securities. To avoid the non-trading problem, and also to determine the extent of the Monday phenomenon across securities, they conduct tests on individual securities. These individual tests still reveal a negative mean on Mondays for all the individual securities. To avoid heteroskedasticity, their model is standardised by the estimated standard deviations for each day of the week.

Gibbons and Hess (1981) conclude that day-of-the-week effects definitely exist in S & P's asset returns. The most obvious effects manifest in the form of negative mean returns on Mondays for stocks and below-average returns for bills on Mondays. Gibbons and Hess (1981) provides no satisfactory reason for these findings.

4.3.2 Keim and Stambaugh (1984)

Keim and Stambaugh (1984) extend the study of the day-of-the-week effect by extending the total research period to 55 years. They also examine additional stocks, such as those of small firms (low capitalisation) and those traded OTC. Keim and Stambaugh (1984) make use of S & P Composite index returns and reassert the fact that the data exhibits a weekend effect.

Keim and Stambaugh (1984) also investigate the possible relationships between firm size and the weekend effect. To test equality of mean returns across days of the week, and across portfolios, they estimate a system of unrelated regressions:

$$R_{pt} = \sum_{i=1}^{5} \alpha_{pi} D_{it} + \varepsilon_{pt} \qquad p = 1, \ldots, 10; \qquad t = 1, \ldots, T, \qquad\qquad (4.2)$$

where d_{it} is a dummy variable that is equal to 1 for day i and 0 otherwise. The hypothesis of equality of mean returns across days for a particular portfolio p is $\alpha_{p1} =$ $\alpha_{p2} = \alpha_{p3} = \alpha_{p4} = \alpha_{p5}$.

Even though they find weekend effects for all firm sizes, their results indicate that the stocks of smaller firms have a greater tendency for average returns to be high on a Friday. Although no formal test supports their supposition, they conclude that their findings are explained by some form of upward bias in week-ending prices that is reversed on Mondays.

They continue, by hypothesising that the higher-than-average stochastic disturbance (error) terms of their model on Fridays, tend to produce lower-than-average returns on Mondays. This behaviour implies a lower correlation between a Friday's return and Monday's return, than between returns on other successive days. They once again prove a Monday effect in the U.S. market.

4.3.3 Jaffe and Westerfield (1985)

The day-of-the-week effect has also been investigated for both international equity markets and international non-equity financial markets. Studies by Jaffe and Westerfield (1985) reveal significant negative mean returns on Mondays in the U.S., Canadian and the UK stock markets. They also find significant negative Tuesday returns in the Japanese and Australian stock markets.

Jaffe and Westerfield (1985) build on the work of French (1980), Gibbons and Hess (1981), and Keim and Stambaugh (1984) in constructing their regression model for each country. Their results indicate that, after allowing for the common effects in the U.S. stock market, there is a significant independent seasonal pattern in the return distributions of each country. They conclude that foreign investors investing in the U.S.

confront a weekend effect in their respective stock markets independent of the weekend effect in the U.S. While the time zone 'theory' explains some of the Australian seasonal patterns, it does not explain the Japanese seasonal patterns.

4.3.4 Chang, Pinegar and Ravichandran (1993)

In their study of the day-of-the-week effect, Chang *et al.* (1993) challenge the findings of Connolly (1989, 1991) that suggest that the day-of-the-week effect disappeared from the U.S. market after 1975. In their study, Chang *et al.* (1993) make use of index data from The FT-Actuaries World Indices $^{TM/SM}$. Their data stretched from 1 January 1986 through to 30 April 1992, thereby including the same data used by Connolly (1989, 1991).

The equity return data taken from The FT-Actuaries World Indices $^{TM/SM}$ included nearly 2 500 stocks from 24 countries, 11 geographic regions, 7 economic sectors and 36 industry groups. These stocks represented approximately 76 percent of the total value of the world's equity markets by March 1990. Also, the market value of the firms in the indices exceeds $ 100 million. By only including firms with a market value of $ 100 million and more, it is ensured that the equity indices represent investment opportunities that are actually available and likely to be taken by foreign investors.

Although they find Connolly's evidence of a non-existent effect in the U.S. market to be substantial, a day-of-the-week effect is present in five European markets (France, Italy, Spain, Sweden and the Netherlands). According to Chang *et al.* (1993) equities markets in Hong Kong and Canada also show day-of-the-week effects.

Their findings do, however, pose a further challenge to the investigation of the day-of-the-week effect over global markets. That they include factors such as the diverse institutional arrangements within Europe, and the various sizes of the firms in their sample as well as the difference in market-making processes confirms that delayed responses to adverse information as discussed by Damodaran (1989) are not true for

their results. This leaves them with the same conundrum as Jaffe and Westerfield (1985) pertaining to the reason for this day-of-the-week effect in the market.

4.3.5 Cornell (1985)

Cornell (1985) investigates the possibility of the existence of a day-of-the-week effect in the S & P 500 index and the most actively traded futures contract. Cornell's (1985) results confirm the findings of Rogalski (1984) regarding the weekly patterns of returns for the S & P 500 index, but reveal no similar pattern for the S & P 500 futures contracts.

Cornell (1985) finds a statistically significant weekly seasonal pattern in the basis (the logarithm of the futures price minus the logarithm of the spot price of a futures contract), which tends to widen on Mondays and narrow on Tuesdays. This weekly pattern is due to the peculiar behaviour of cash prices of futures contracts during non-trading hours.

Although transaction costs are lower in the futures market and the futures data more closely approximate the true market prices, previous studies showed that neither measurement error nor transaction costs can explain the pattern in the cash prices of futures contracts. Furthermore, he finds no evidence to suggest that futures contracts prices deviate from the predictions of the efficient market hypothesis.

In addition, Cornell (1985) investigates the relationship between the seasonal patterns observed in the cash market and the futures market. Although there is a relationship between the cash market and the futures market, this relationship has changed over time and thus serves as a possible explanation for the lack of a seasonal effect in the futures market. Another repudiating factor is the fact that transaction costs, especially the cost of selling short, are much smaller in the futures market. A final reason for the lack of a seasonal pattern in futures prices is that, the volumes of futures contracts traded in the first and in the final minutes of the day are very high and therefore representative of true market prices.

4.3.6 Flannery and Protopapadakis (1988)

Flannery and Protopapadakis (1988) address the question of how uniform intra-week data and other seasonal patterns are across U.S. common stocks and Treasury securities. Through documenting intra-week seasonality for eleven assets (Treasury securities, Repurchase rates and stock market indices) between 1976 and 1984, they find that the returns on the assets show substantial seasonality over this period. They also find negative stock returns on Mondays and that Monday's mean Treasury securities returns are smaller than any other day's for all Treasury security maturities. Monday's returns are furthermore found to become more negative as the Treasury security's maturity increases.

Flannery and Protopapadakis (1988) state that return seasonality is not uniform across securities and that Treasury securities as a group have markedly different seasonal patterns from stocks as a group. This indicates that intra-week returns seasonality is unlikely to derive exclusively from broad economic forces that affect all asset markets similarly. Seasonal patterns are also found to be different across similar securities.

In analysing S & P 500 stock indices, Flannery and Protopapadakis (1988) find that these indices exhibit substantially different Thursday and Friday deviations from their own overall mean returns, and Treasury securities return deviations differ from one another on Monday and on Wednesday. The fact that similar securities exhibit significantly different seasonal patterns suggests that market-specific, institutional features cannot explain all seasonality. Given these results, Flannery and Protopapadakis (1988) deduce that there appears to be no explanation for return seasonality.

Finally, they conclude that there might be a unified explanation for the intra-week seasonality in asset prices as well as negative Monday returns. The particular pattern of Treasury securities' Monday returns is consistent with intra-week variations in the market discount rates' term premia. If term premia systematically rose over the

weekend, longer term securities would be affected more substantially (which is supported by their findings).

4.3.7 French, Schwert and Stambaugh (1987)

In their study, French *et al.* (1987) examine the relationship between stock returns and stock market volatility, based on the daily values of the S & P's composite portfolio for the period 1928 to 1984. In addition, they investigated whether or not the expected market risk premium (Litterman, 2003:42 defines risk premium as expected returns on a stock market portfolio minus the risk-free interest rate) is positively related to risk as measured by the volatility of the stock market returns.

In order to investigate the relationship between expected stock returns and volatility, French *et al.* (1987) make use of two statistical approaches. In the first, they use daily stock returns to compute estimates of monthly volatility. These estimates are then decomposed into predictable and unpredictable components by making use of univariate autoregressive integrated moving average (ARIMA) models.

They find that regressions of monthly excess holding period returns on the predictable component provided little evidence of a positive relation between *ex ante* volatility and expected risk premiums. However, they do find evidence of a strong negative relation between excess holding period returns and the unpredictable component of volatility.

In their second statistical approach, French *et al.* (1987) use daily returns to estimate *ex ante* measures of volatility with a GARCH model. They make use of a GARCH-in-Mean (GARCH-M) model to estimate the *ex ante* relation between risk premiums and volatility.

Their results indicate that the expected market risk premium is positively related to the predictable volatility of New York Stock Exchange (NYSE) common stock returns over the 1928 to 1984 period.

French *et al.* (1987) state that, if expected risk premiums are positively related to predictable volatility, future expected risk premiums will increase; while current stock prices will decrease in the event of a positive unexpected change in volatility. This negative relation provides indirect evidence of a positive relation between expected risk premiums and volatility. Because an increase in volatility translates to an increase in stock prices, investors (such as hedge fund managers) should avoid making key trades in high volatility conditions.

4.3.8 Akgiray (1989)

Akgiray (1989) makes use of the daily returns on the CRSP value-weighted and CSRP equal-weighted indices covering the period from January 1963 to December 1986. Returns are given by:

$$R_t = \log(I_T/I_{t-1}), \qquad\qquad\qquad (4.3)$$

where I_T is the points value of the index and the dividends are part of total value. For small values of R_t, such as in daily data, this definition is very similar to the arithmetic rate of return.

Akgiray (1989) presents empirical evidence that indicates that time-series of daily stock returns exhibit considerable levels of dependence. It is, therefore, important to check time-series data for autocorrelated stochastic disturbance terms when fitting autoregressive models on returns data.

The daily return series exhibit statistically significant levels of second-order dependence and can as a result not be modelled as linear white-noise processes. A reasonable return-generating process is empirically shown to be a first-order autoregressive process with conditionally heteroskedastic innovations. Although Akgiray (1989) finds that GARCH(1,1) processes fit stock return data most satisfactorily, forecasts of such data based on any GARCH model are found to be superior.

GARCH models may also be used to further the understanding of the relationship between volatility and expected returns. Since the fundamental valuation theories in finance are based on a hypothesised risk-return relationship, they hold for the average security but do not explain the full valuation mechanism of 'non-average' securities. The apparent failure of the models for such securities may be largely due to an erroneous choice of values for the model parameters. Consequently, improved parameter estimates may explain the discrepancies between theory and reality. In this regard, Akgiray (1989) finds GARCH models to be very useful for forecasting variance.

4.3.9 Nelson (1991)

In his paper, Nelson (1991) proposes a different kind of GARCH model with which to eliminate some of the restrictive characteristics that make the common GARCH models unfit for explaining changes in the volatility of stock market returns. Nelson (1991) finds that GARCH models may unduly restrict the dynamics of the conditional variance process, because they impose parameter restrictions that are often violated by estimated coefficients. It is also difficult to interpret whether or not shocks to conditional variance persist because the usual norms for measuring persistence often do not agree. Nelson (1991) explains how changes to Bollerslev's GARCH model (equation 4.4 below) can enhance it so as to eliminate the abovementioned shortcomings.

In the first phase, Nelson states that Bollerslev's GARCH model adds to Engle's original ARCH model by making the variance parameter (σ_t^2) linear in lagged values of the error term ε_t^2, where $\varepsilon_t^2 = \sigma_t^2 z_t^2$. The model is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{p} \alpha_j z_{t-j}^2 \sigma_{t-j}^2, \qquad (4.4)$$

where ω, α_j and β_i are nonnegative.

He adds the GARCH-M model of Engle and Bollerslev (1986a) the equation of which takes the form of:

$$R_t = \varphi + \delta\sigma_t^2 + \varepsilon_t, \tag{4.5}$$

where σ_t^2, the conditional variance of R_t, enters the conditional mean of R_t as well. If for example, R_t is the return on a portfolio at time t, its required rate of return may be linear in its risk as measured by σ_t^2.

In the second phase, Nelson (1991) extends the GARCH(1,1) model to a multivariate context, and shows how Bollerslev, Engle and Wooldrige (1988) were able to test a conditional capital asset pricing model (CAPM) with time varying covariances of asset returns. By substituting recursively for the $\beta\sigma_{t-i}^2$ terms, this model can assume the following form:

$$\sigma_t^2 = \omega^* + \sum_{k=1}^{\infty} \phi_k z_{t-k}^2 \sigma_{t-k}^2. \tag{4.6}$$

It follows that, if ω, α_j and β_i are nonnegative, ω^* and the ϕ_k are also nonnegative. By setting the conditional variance equal to a constant plus a weighted average (with positive weights) of past squared residuals, GARCH models elegantly capture the volatility clustering in asset returns. This characteristic makes GARCH models ideal for testing volatility patterns in market returns.

Nelson (1991) proceeds to explain why this integrated model structure still imposes significant limitations on GARCH models. He states that there is evidence that stock returns are negatively correlated with changes in returns volatility (volatility tends to rise in response to 'bad' news and fall in response to 'good' news), which he addresses with his exponential GARCH (EGARCH) model.

Nelson (1991) continues explaining that the reason for these limitations is that GARCH models assume that only the magnitude and not the positivity or negativity of unexpected excess returns determines feature σ_t^2.

If the distribution of z_t is symmetric, the change in variance tomorrow is conditionally uncorrelated with excess returns today. In equation 4.4 above, σ_t^2 is a function of lagged z_t^2, and so is invariant to changes in the algebraic sign of the z_t's. It can thus be inferred, that only the size, and not the sign of lagged residuals determines conditional variance. This suggests that a model in which σ_t^2 responds asymmetrically to positive and negative residuals might be preferable for asset pricing applications. This is, therefore significant for testing volatility patterns in market returns.

Nelson (1991) points out a second limitation of GARCH models resulting from the nonnegativity constraints on ω^* and the ϕ_k in equation 4.6 above, which are imposed to ensure that σ_t^2 remains nonnegative for all t-values with probability 1. These constraints imply that increasing z_t^2 in any period increases σ_{t+m}^2 for all $m \geq 1$, ruling out random oscillatory behaviour in the σ_t^2 process.

A third shortcoming of GARCH modelling concerns the interpretation of the 'persistence' of shocks to conditional variance. If volatility shocks persist indefinitely, they may shift the whole term structure of risk premia, and therefore are likely to have a significant impact on investment in long-lived capital goods. It is found that in GARCH(1,1) models, shocks may persist in one norm and die in another; therefore the conditional moments of GARCH(1,1) may explode, even when the process itself is strictly stationary (Nelson, 1990a). This may lead to difficulties when the parameters for the model are being determined.

If σ_t^2 is to be the conditional variance of ε_t given information at time t, it must be nonnegative with probability 1. As stated above, GARCH models achieve this by making σ_t^2 a linear combination (with positive weights) of positive random variables.

Nelson (1991) makes use of a different approach to ensure that σ_t^2 remains nonnegative. He does this by making $\ln(\sigma_t^2)$ linear in some function of time and lagged z_t's for some suitable function g:

$$\ln(\sigma_t^2) = \alpha_t + \sum_{k=1}^{\infty} \beta_k g(z_{t-k}), \qquad \beta_1 \equiv 1, \tag{4.7}$$

where $\{\alpha_t\}_{t\,=\,-\infty,\,\infty}$ and $\{\beta_k\}_{k\,=\,1,\,\infty}$ are real, non-stochastic, scalar sequences. To accommodate the asymmetric relation between stock returns and volatility changes, the value of $g(z_t)$ must be a function of both the magnitude and the sign of z_t. He does so by making $g(z_t)$ a linear combination of z_t and $|z_t|$:

$$g(z_t) \equiv \theta z_t + \gamma \left[|z_t| - E|z_t| \right], \tag{4.8}$$

$$z_t = \varepsilon_t / \sqrt{\sigma_t}. \tag{4.9}$$

The two components of $g(z_t)$ are θz_t and $\gamma\left[|z_t| - E|z_t|\right]$, each with mean zero. The term $\gamma\left[|z_t| - E|z_t|\right]$ determines the size effect and the term θz_t determines the sign effect of innovations. If the distribution of z_t is symmetric, the two components are statistically independent. Over the range $0 < z_t < \infty$, $g(z_t)$ is linear in z_t with slope $\theta + \gamma$, and over the range $-\infty < z_t \leq 0$, $g(z_t)$ is linear with the slope $\theta - \gamma$. Thus, $g(z_t)$ allows the variance process $\{\sigma_t^2\}$ to respond asymmetrically to rises and falls in stock price.

If it is then assumed that $\gamma > 0$ and $\theta = 0$, the innovation in $\ln(\sigma_{t+1}^2)$ would be positive (negative) when the magnitude of z_t is larger (smaller) than its expected value. If, on the other hand $\gamma = 0$ and $\theta < 0$, the innovation in conditional variance would be positive (negative) when returns innovations are negative (positive). The exponential form of GARCH thus remedies the incapacity of the GARCH(1,1) model to explain the positivity and negativity of unexpected excess returns.

With respect to the second limitation, Nelson points out that there are no inequality constraints in equations 4.7 and 4.8 and that the β_k terms can be both negative and positive.

Nelson's (1991) final criticism of GARCH models is that it is difficult to evaluate whether or not shocks to variance persist or not. In the exponential GARCH model, however, $\ln(\sigma_t^2)$ is a linear process and its stationarity (covariance or strict) and ergodicity are easily checked. If the shocks to $\{\ln(\sigma_t^2)\}$ die out quickly enough, and if the component $\{\alpha_t\}$ is removed, then $\{\ln(\sigma_t^2)\}$ is strictly stationary and ergodic. These stationarity and ergodicity criteria are exactly the same as for a general linear process with finite innovations variance, thereby solving the third drawback.

For this reason Nelson (1991) provides a superior GARCH type model with which the volatility patterns in the South African All-Share index data can be modelled. Ogum *et al.* (2002) make use of Nelson's (1991) EGARCH model to examine the existence of a day-of-the-week effect in the Kenyan market.

4.3.10 Ogum, Nouyrigat and Beer (2002)

In their article, Ogum *et al.* (2002) explore four time properties that emerge from the empirical time-series literature on asset returns on the Nairobi Stock Exchange (NSE) Kenya. They examine the predictability of stock returns from past observations, the autoregressive behaviour of conditional volatility, the asymmetric response of conditional volatility to innovations and the conditional variance risk premium, in order to assess whether or not a day-of-the-week effect exists in the Kenyan market.

For their analysis, Ogum *et al.* (2002) make use of the EGARCH model, first suggested by Nelson (1991). Ogum *et al.* (2002) make use of Nelson's (1991) EGARCH model to eliminate the fact that returns of equal magnitude may exhibit asymmetric conditional variance behaviour in the sense that negative shocks generate more volatility than positive shocks. The use the more general GARCH models does not allow for this elimination.

Ogum *et al.* (2002) follow Nelson (1991) in allowing for the asymmetric response of volatility to innovations for 'in-Mean' effects by making use of his EGARCH-M model. This EGARCH-M (p,q) captures skewness and asymmetry. In this formulation,

the conditional variance is an exponential function of the previous conditional variances and excess returns. Ogum *et al.* (2002) introduce autoregressive (AR) dynamics into the mean equation to capture the effect of non-synchronous trading, which gives rise to a positive first order autocorrelation in market returns. Their model follows an AR(2) process and is given as:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \phi_2 R_{t-2} + \delta\sigma_t + \varepsilon_t, \qquad (4.10)$$

where R_t represents the measure of market returns. In this equation R_t is considered to be linearly related to the previous two days' market returns and its own standard deviation (σ_t). The error term is represented by ε_t and is assumed to follow a normal distribution. The 'in-Mean' parameter (δ), which follows Engle *et al.* (1987) is introduced into the main equation, in order to determine whether or not investors are rewarded for their exposure to market risk. The (δ) in subsequent equations is referred to as the risk factor.

Ogum *et al.* (2002)'s findings indicate that asymmetric volatility found in the U.S. and the UK does not seem to be a universal appearance. Instead they find the asymmetric volatility coefficient to be significantly positive in the NSE, thus suggesting that positive shocks increase volatility more than negative shocks of the same magnitude.

4.3.11 Conclusion

The various studies detailed investigate the day-of-the-week effect by testing seasonal patterns in stock returns, volatility, various markets and a variety of financial instruments. The majority of the studies investigating the day-of-the-week effect in stock returns employ the standard ordinary least-squares (OLS) methodology by regressing the returns on five daily dummy variables (Chang *et al.*, 1993; Cornell, 1985; Keim & Stambaugh, 1984, and Gibbons and Hess, 1981).

OLS regression analysis is based on several statistical assumptions. One key assumption is that the errors are independent of each other. Using time-series data,

however, has two major drawbacks. The first is that the errors in the model may be autocorrelated and the second is that error variances may be time-dependent as opposed to being constant, thus implying heteroskedasticity. If the error term is autocorrelated, the efficiency of OLS parameter estimates is adversely affected and standard error estimates are biased.

In order to address the issue of autocorrelation, lagged values of the dependant variable can be included in the equation (Berument & Kiymaz, 2001:3). Such a model assumes that returns (as dependant variable) have the following stochastic process:

$$R_t = \alpha_0 + \alpha_1 M_t + \alpha_2 Tu_t + \alpha_3 Thu_t + \alpha_4 Fri_t + \sum_{i=1}^{P} \beta_i R_{t-i} + \varepsilon_t, \qquad (4.11)$$

where R_t represents returns; M_t, Tu_t, Thu_t and Fri_t are the dummy variables for Monday, Tuesday, Thursday, and Friday at time t. $M_t = 1$, if day t is a Monday and 0 otherwise; $Tu_t = 1$, if day t is a Tuesday and 0 otherwise, etc. The stochastic disturbance (error) term is indicated by ε_t.

In order to address the problem of heteroskedasticity in error terms, variances of errors are allowed to be time-dependent, so as to include a conditional heteroskedasticity that captures time variation of variance in stock returns. Hence, error terms now have a mean of zero and a time changing variance of σ_t^2 ($\varepsilon_t \sim (0, \sigma_t^2)$). To achieve this, the data can be modelled with a conditional heteroskedastic model (Berument & Kiymaz, 2001:9).

The literature suggests various conditional heteroskedasticity models. As previously mentioned, the prominent two are the ARCH and GARCH models. Engle *et al.* (1987) also introduce the ARCH-M methodology, which allows the conditional standard errors (or variance) to affect returns. French *et al.* (1987) make use of a GARCH-M model to test the relationship between stock returns and stock market volatility. In recent studies, GARCH(1,1)-M was decided upon as an appropriate model for financial data (Litterman, 2003:245).

Nelson (1991), however, finds various shortcomings with the general GARCH(1,1) models (see section 4.3.9). Firstly, because GARCH models assume that only the magnitude and not the positivity or negativity of unexpected excess returns determines feature σ_t^2, they rule out the possibility of a negative correlation between current returns and future returns volatility. Secondly, GARCH models impose parameter restrictions which are often violated by estimated coefficients; this may unduly restrict the dynamics of the conditional variance process. Thirdly, with GARCH models it is often difficult to assess whether or not shocks to conditional variance persist. Ogum *et al.* (2002) make use of the EGARCH models developed by Nelson (1991) in order to examine the autoregressive behaviour of conditional volatility on the NSE (Kenya). By making use of Nelson's model, Ogum *et al.* (2002) manage to eliminate the major shortcomings of typical GARCH models.

This dissertation, therefore, takes the findings of Nelson (1991) into consideration in deciding upon a final model in order to determine the day-of-the-week effect. In the next section the data modelled is discussed and the process followed in deriving the final model is detailed.

4.4 Data and Methodology

In this section, the data is tested for seasonality by implementing an appropriate statistical model, in order to determine whether or not a day-of-the-week effect exists in the South African market. This model is derived from the articles discussed above, and by making use of several statistical procedures in SAS® (SAS Institute Inc., 2003).

4.4.1 Data

The data consists of the daily (end-of-the-day) index returns of the Johannesburg Stock Exchange's (JSE) All-Share index from 30 May 2000 to 27 May 2005 (JSE, 2005). The data consists of time-series index returns (prices) as well as volumes traded in terms of quantity as well as rand values. There are 1248 observations, excluding all trading holidays and weekends. Because of the various trading holidays, the number of

observations varies for every day of the week. For the period of observation, there were 241 observations for Monday, 252 observations for Tuesday, 251 observations for Wednesday, 253 observations for Thursday and 250 observations for Friday.

Graph 4.1 below, illustrates the growth of the South African All-Share index from 30 May 2000 to 27 May 2005. The graph indicates that the South African All-Share index has had positive growth from May 2003 onwards.

GRAPH 4.1   THE SOUTH AFRICAN ALL-SHARE INDEX RETURNS
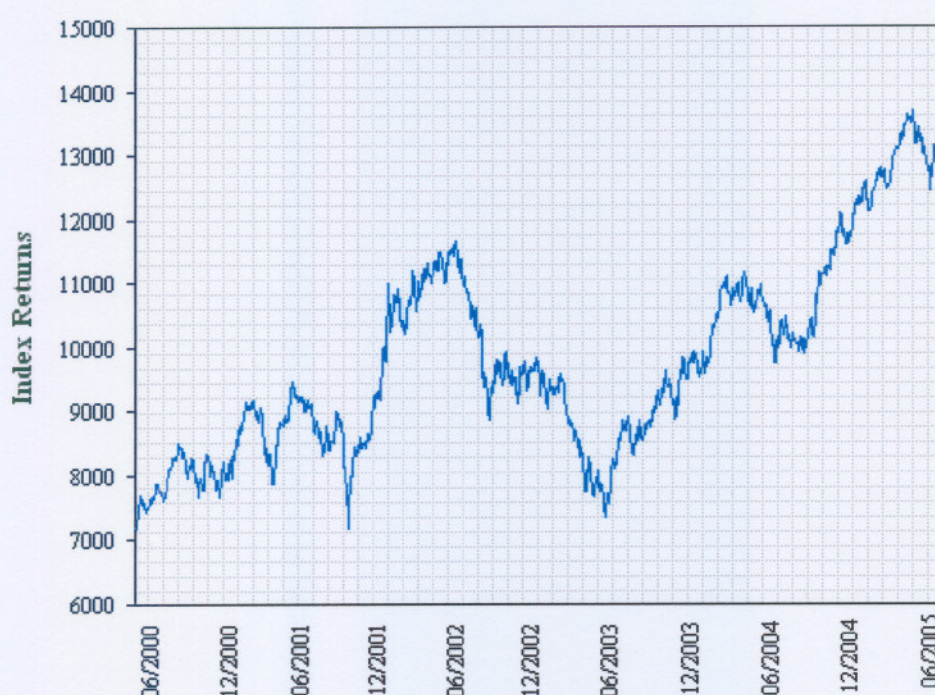
(JSE, 2005)

Returns (R_t) are expressed in the local currency and are calculated as the first differences in natural logarithms of the All-Share index returns (prices) multiplied by 100:

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

(4.12)

where R_t is the return for the period t; P_t is the daily closing index prices at time t, and t is the time measured in days. Therefore, each return series is expressed as a percentage. Modelling an index in this manner is typical in the literature (see for example Nelson, (1991)). The sample description of returns is outlined in Table 4.1 (section 4.4.2.3).

Graph 4.2 below, illustrates the daily index mean returns on the South African All-Share index expressed as the logarithm of the P_t/P_{t-1}, which is equal to R_t.

GRAPH 4.2   SOUTH AFRICAN ALL-SHARE INDEX MEAN RETURNS
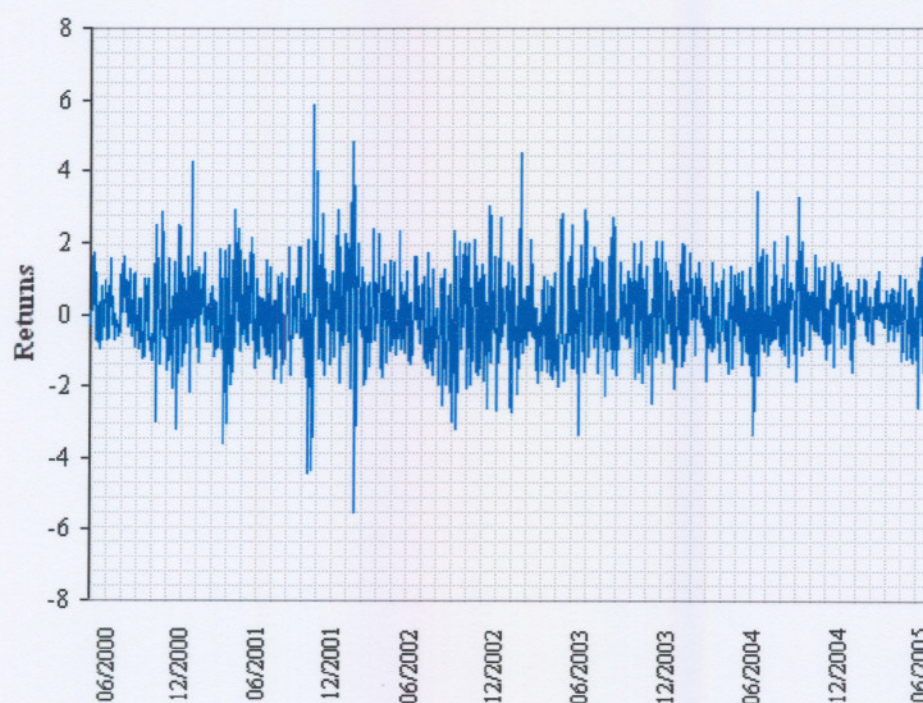
(JSE, 2005)

The next section covers the development of the model which is used to investigate the day-of-the-week effect. The final model was derived by making use of the literature that was discussed above as well as various SAS® procedures (SAS Institute Inc., 2003). It is to be noted that other models are also tested to ensure objectivity. To ascertain which one best models the day-of-the-week effect, these models will be tested

by means of various statistical measures to ascertain their statistical appropriateness. These statistical measures will be discussed in section 4.4.2 below. After deciding on the final model, it will be used to examine the South African All-Share index data in order to affirm whether or not a day-of-the-week effect is present in the data. This model will also be tested to ensure statistical appropriateness.

4.4.2 Methodology

4.4.2.1 Estimating Procedure of the Model

In testing for day-of-the-week effects, a variety of models can be employed. Two types of models will be used in this dissertation. The first type of model allows the inclusion of all five days in the model as dummy variables. In such a case a restriction on the parameter estimates have to be included to avoid the dummy variable trap.[18] The model is given by:

$$R_t = \alpha_0 + \alpha_1 M_t + \alpha_2 Tu_t + \alpha_3 Wed_t + \alpha_4 Thu_t + \alpha_5 Fri_t + \varepsilon_t,$$ (4.13)

with restriction $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5 = 0$.

Market return is given by R_t while M_t, Tu_t, Wed_t, Thu_t and Fri_t are dummy variables for Monday, through Friday at time t; and ε_t represents the error term. For the daily dummy variables: $M_t = 1$, if day t is a Monday and 0 otherwise; $Tu_t = 1$, if day t is a Tuesday and 0 otherwise; $Wed_t = 1$ if, day t is a Wednesday and 0 otherwise; $Thu_t = 1$ if, day t is a Thursday and 0 otherwise; and $Fri_t = 1$ if, day t is a Friday and 0 otherwise.

The second type requires that one of the days be left out to ensure avoidance of the dummy variable trap. This model is given by:

$$R_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i D_{it} + \varepsilon_t,$$ (4.14)

---

[18] The dummy variable trap is a situation of perfect colinearity or perfect multi-colinearity, should there be more than one exact relationship between the variables (Gujarati, 2003: 302).

where one of the days is left out of the model. D_{it} is a dummy variable that is equal to 1 for day i and 0 otherwise. Following Gibbons and Hess (1981), the latter was used first to test for the day-of-the-week effect in the South African All-share index data. To test for the day-of-the-week effect in the South African All-share index data, the Wednesday is left out in this equation.[19] This model was tested for both autocorrelation and heteroskedasticity. Testing for autocorrelation was done by making use of the *DWPROB*-option in the PROC AUTOREG procedure of SAS® (SAS Institute Inc., 2003). Heteroskedasticity was simultaneously tested by making use of the ARCHTEST option in the PROC AUTOREG procedure of SAS® (SAS Institute Inc., 2003). More regarding the test for heteroskedasticity follows later.

In the case of equation 4.14 above, the Durbin-Watson statistics for higher-order autocorrelation was used to test for autocorrelation in the daily OLS residuals. It is advisable to specify an order larger than the largest expected autocorrelation. For equation 4.14, 6 orders were specified for daily data because the largest expected autocorrelation is 5 days for a weekly effect. This test does not, however, specify which autoregressive orders should be tested, but only indicates that autocorrelation of this (or higher) order is present in the log returns. It was found that the first-order Durbin-Watson test is statistically significant at the 5 percent level of significance, with a *p-value* < .0001 for the hypothesis of first-order autocorrelation. Since the first-order Durbin-Watson test was found to be significant, the tests for the higher orders can be ignored. The above results call for autocorrelation correction. In order to address the issue of autocorrelation Berument and Kiymaz (2001:3) is followed by inserting lags in the return equation.

Autocorrelation is found to be particularly severe in emerging markets data because of their low level of liquidity (DeSantis & Imrohoroglu, 1997). This explains the existence of autocorrelation in the South African All-Share index data. The complete report

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[19] Wednesday has been elected for elimination from the regression. Since Wednesday is being left out, all the other days of the week are expressed in terms of Wednesday. This exercise is repeated for Monday, Tuesday, Thursday and Friday. The results of the tests for the other days of the week can be viewed in table 4.4 below.

indicates that autocorrelation was present in the data.[20] In order to decide on the number of autoregressive orders to be used, the stepwise autoregressive process was performed by making use of the Yule-Walker method (Maddala, 2002:521-522). An initial order of 6 was used to include a lag for every day of the week for which their might be autocorrelation. This process was also performed in SAS[®] by making use of the BACKSTEP-option in SAS[®]'s PROC AUTOREG procedure (SAS Institute Inc., 2003).

The test revealed that lags (1 and 3) were statistically significant at the 5 percent level of significance. The results of the test thus indicate that an AR (3) process should be used to test for seasonality in the All-Share index data. Once the lags of the dependant variable R_t have been inserted, the returns equation will take the form of equation 4.15 below.[21]

The data was simultaneously tested for heteroskedasticity by making use of the ARCHTEST option in the PROC AUTOREG procedure in SAS[®] (SAS Institute Inc., 2003). The Q statistics test for changes in variance across time was performed using lag windows ranging from 1 through 12.[22] These tests strongly indicate heteroskedasticity, with $p < 0.0001$ for all lag windows. In the second column the Lagrange multiplier (LM) tests also indicate heteroskedasticity. Heteroskedastic errors are eliminated by modelling the variance of the returns with Nelson's (1991) EGARCH(1,1) model.

Derivation of the next model now follows and a discussion with reference to its descriptive statistics follows thereafter. This model is derived from various studies in the literature (as discussed in section 4.2 above) as well as the empirical research undertaken and detailed above.

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[20] This can be viewed in Statistical Report 1.1, see the annexure
[21] The complete report can be viewed in Statistical Report 1.3, see the annexure.
[22] The complete PROC AUTOREG output indicating heteroskedasticity can be viewed in Statistical Report 1.2, see the annexure.

4.4.2.2 The Model

This dissertation makes use of a GARCH model to account for both autocorrelation and heteroskedasticity, and follows Nelson (1991) and Ogum *et al.* (2002) in allowing for the asymmetric response of volatility to innovations; and Engle *et al.* (1987) in making use of 'in- Mean' (risk factor) effects. As previously mentioned, Nelson (1991) introduced EGARCH to counter the asymmetric conditional variance behaviour of returns brought about by the "leverage effect" (Black, 1976). Nelson's (1991) EGARCH(p,q) model captures skewness and asymmetry.

The first GARCH model takes the form of an AR(3) EGARCH(1,1)-M model and can be written as:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \phi_i R_{t-i} + \alpha_2 M_t + \alpha_3 Tu_t + \alpha_4 Thu_t + \alpha_5 Fri_t + \delta \sigma_t + \varepsilon_t, \qquad (4.15)$$

$$\varepsilon_t \,|\Omega_{t-1} \sim N\left(0, \sigma_t^2\right), \qquad (4.16)$$

$$\ln\left(\sigma_t^2\right) = \varphi_0 + \varphi_1 \left\{ \left| \varepsilon_{t-1}/\sigma_{t-1} \right| - \sqrt{2/\pi} \right\} + \gamma \varepsilon_{t-1}/\sigma_{t-1} + \beta \ln\left(\sigma_{t-1}^2\right), \qquad (4.17)$$

where equation 4.15 is the return equation, equation 4.16 indicates how the error terms are distributed and equation 4.17 is the variance equation. In equation 4.15, R_t represents the measure of market return, M_t, Tu_t, Thu_t and Fri_t are dummy variables recording Monday, Tuesday, Thursday, and Friday at time t. $M_t = 1$ if day t is a Monday and 0 otherwise; $Tu_t = 1$ if day t is a Tuesday and 0 otherwise, etc. R_t is considered to be linearly related to the previous days' index returns and its own standard deviation (σ_t). The component $\alpha_i R_{t-1}$ allows for the returns on the present day to be influenced by the returns of one period (day) prior. The stochastic disturbance (error) term is indicated by ε_t.

As stated above, the error term (ε_t) is assumed to follow a normal distribution with Ω_{t-1} being the set of relevant information available at time t. Following Engle *et al.* (1987), the equation also allows for a risk factor in the form of the 'in-Mean' parameter

(δ). This parameter is introduced in order to determine whether or not investors are rewarded for their exposure to market risk. According to the CAPM mean-variance hypothesis, large standard deviations (variances or volatility) are expected to be associated with large returns (Litterman, 2003:37). Hence, it follows that (δ) is expected to be greater than zero. Consequently the parameter (δ) determines the relationship between returns and volatility.

The conditional variance equation 4.17 follows an EGARCH(1,1) process (Nelson, 1991), which allows for time-varying heteroskedasticity in the errors. The AR(3) EGARCH(1,1)-M model is more general than the standard GARCH model, in that it allows innovations of different signs to have a differential impact on volatility and allows bigger shocks to have a larger impact on volatility. This model is further improved by modelling the logarithm of the conditional variance (σ_t), eliminating the need to restrict parameter values to avoid negative variances.

In equation 4.17 the parameter (φ_j) measures the impact of innovation on conditional volatility at time t. The parameter (γ) permits the asymmetric response of conditional variance to innovations of a differing sign (positive or negative). In the case of (γ) in equation 4.17 being negative, negative realisations of the innovation (risk factor) in equation 4.15 will generate more volatility than positive realisations will. If, however, (γ) is positive, negative realisations of the innovation in equation 4.15 will generate less volatility than positive realisations will.

The presence of the leverage effect can be tested by the assumption that $\gamma < 0$. The impact is asymmetric in the case where $\gamma \neq 0$ and the most recent residual term impact is exponential, rather than quadratic. 'Good' news $(\varepsilon_{t-1} > 0)$ will have an impact of $(\varphi + \gamma)/\sigma_{t-1}$ while 'bad' news $(\varepsilon_{t-1} < 0)$ will have an impact of $(\varphi - \gamma)/\sigma_{t-1}$) (Ogum et al., 2002:11). The parameter (β) is the autoregressive term on lagged conditional volatility, thus reflecting the weight given to the previous period's conditional volatility in the conditional volatility at time t. It measures the persistence of shocks to the

conditional variance. Graph 4.3 below, illustrates the heteroskedastic nature of the data over the period of 30 May 2000 to 27 May 2005.

GRAPH 4.3 CONDITIONAL VARIANCE IN THE SOUTH AFRICAN INDEX RETURNS DATA
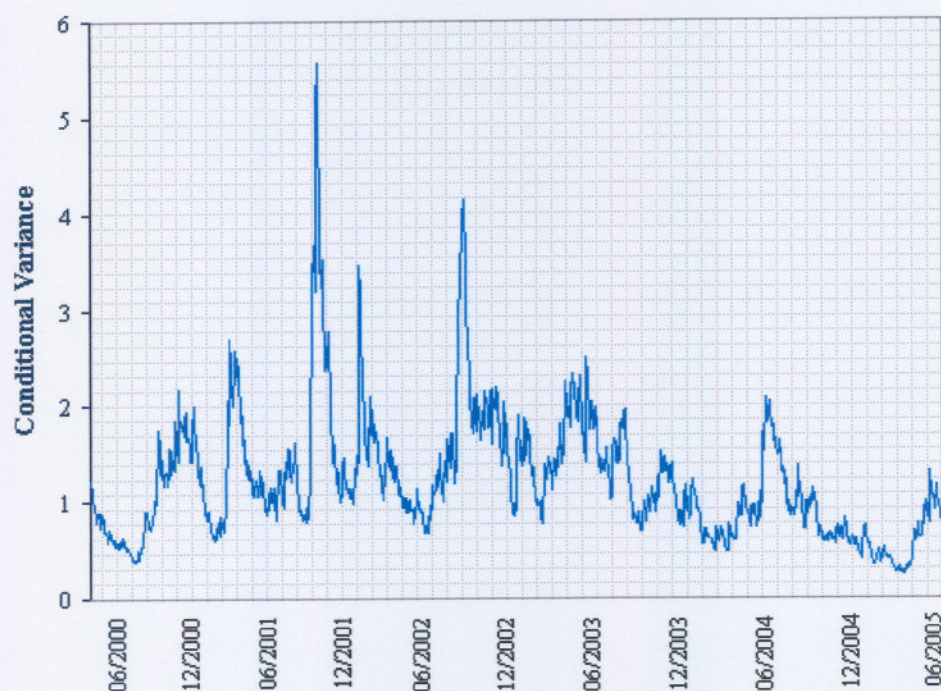
(JSE, 2005)

It should be noted that the model consisting of equations 4.15 through 4.17 above, was the first GARCH model within this study, used to test for the existence of a day-of-the-week effect in the South African All-Share index returns data. In order to ensure that the most appropriate model is used to test for this effect in the South African market, other models are also tested and their descriptive statistics described in the next section.

4.4.2.3 Results

Before a discussion of the results of the various models employed in this dissertation, a brief description of the data is first detailed.

Table 4.1 below, reports the preliminary statistics (evidence) for the returns of the entire study period, as well as the returns for each day of the week. The first column in Table 4.1 reports the daily mean returns; median, minimum and maximum values; standard deviation; skewness and kurtosis measures for all the days of the week. The mean returns for the entire study period is 0.0520 with a standard deviation of 1.1134.[23]

TABLE 4.1   SUMMARY STATISTICS: SOUTH AFRICAN ALL-SHARE INDEX RETURNS

	All days	Monday	Tuesday	Wednesday	Thursday	Friday
No of obs.	1248	241	252	251	253	250
Mean	0.0520	0.1154	0.0663	-0.0854	0.1215	0.0489
Median	0.0430	0.1528	0.0169	-0.1298	0.0640	0.0599
Maximum	5.8872	2.9202	5.8872	3.4582	4.2921	4.8454
Minimum	-5.5385	-3.3511	-2.884	-4.4457	-4.3249	-5.5386
Std. Dev	1.1134	1.0303	1.1441	1.0975	1.2011	1.0763
Skewness	0.1096	-0.2361	0.6973	-0.0771	0.1607	-0.2046
Kurtosis	2.0034	0.4530	3.0068	1.3809	1.3574	3.6903

Table 4.1 also reports the descriptive statistics for the return series of each day of the week. When the return of each day is analysed, the findings indicate that the mean returns for Thursdays are the highest (0.1215) followed by Mondays with mean returns of 0.1154, while Wednesdays have negative mean returns of -0.0854. Negative skewness is present in the data for Mondays, Wednesdays and Fridays; and positive skewness for Tuesdays and Thursdays. Excess kurtosis is present for returns on Tuesdays and Fridays. The data, thus, suggests that there might be a Thursday effect in mean returns. In order to properly assess the accuracy of this assumption, the data is simulated with an EGARCH model. It is to be noted that this EGARCH-M (p, q) (Nelson, 1991) captures the skewness that was observed in the summary statistics of the data above.

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[23] Volatility is being measured by making use of the standard deviation (Berument and Kiymaz, 2001:184)

The AR(3) EGARCH(1,1)-M model used in this dissertation was derived from the literature and empirically verified by making use of several SAS[®] procedures (SAS Institute Inc., 2003). Equation 4.15 is an extension of equation 4.11, which is an OLS model that allows for lagged values of returns to influence present returns. This extension takes the form of (δ), a risk factor that allows for the interpretation of positive and negative innovations. By making use of an AR(3) EGARCH(1,1)-M model, it was possible to eliminate both autocorrelation and heteroskedasticity from the data.[24] This model was used to test the index returns on the South African All-Share index for cyclical patterns of volatility.[25]

The first column of Table 4.2 below reports the results of the AR(3) EGARCH(1,1)-M. The results indicate that the highest returns are observed on Thursdays (0.2218), while the lowest returns are observed on Tuesdays (0.1168).[26] The estimated returns for every day are positive and statistically significant at the 5 percent level of significance. However, the results from the SAS[®] procedure report that there are negative returns for the second and third lags (SAS Institute Inc., 2003). It was also found that Fridays have the highest volatility (0.0651), indicated by the standard deviation and that Thursdays have the lowest volatility (0.0428).

Furthermore, Table 4.2 indicates that the autoregressive coefficients for lag 1 (R_{t-1}) and lag 3 (R_{t-3}) are significant at the 5 percent level of significance; this, however, is not true of lag 2 (R_{t-2}). This result reaffirms the result of the Yule-Walker method that indicated that only lags 1 and 3 were statistically significant. The AR(3) EGARCH(1,1)-M coefficients are also reported in Table 4.2. Additional models were also tested in order to find a simpler model with which the day-of-the-week effect could be modelled for South African data. This notion of a simpler model is supported by the principle of Parsimony (Beck, 1943:618). The first additional model that was tested was an EGARCH(1,1)-M model with different lags. This model reduced the lags

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[24] The complete report can be viewed in Statistical Report 1.4, see the annexure.

[25] The complete report for the AR(3) EGARCH(1,1)-M model can be viewed in Statistical Report 1.5, see the annexure.

[26] It is to be noted that all the results (mean returns and the volatility of mean returns) are expressed in terms of the absent dummy variable Wednesday.

and thus takes the form of an AR(1) EGARCH(1,1)-M model. As the second autoregressive lag was found to be statistically insignificant at the 5 percent level of significance, no tests were performed with an AR(2) EGARCH(1,1)-M model. Table 4.2 reports a definite Thursday effect present in the South African All-Share index returns when modelled with the AR(1) EGARCH(1,1)-M model. Thursdays have the highest mean returns (0.2295), while Tuesdays have the lowest mean returns (0.1115). The volatility in returns is the highest on Fridays (0.0875) and the lowest on Thursdays (0.0814). These results confirm the results found with the AR(3) EGARCH(1,1)-M model.

The test results show that the 'in-Mean' risk factor (δ) is not significant at the 5 percent level of significance. This result indicates that the incentive for risk takers in the South African market might not be as strong as that in more developed financial markets. In the variance equation the parameter (φ_1) is found to be statistically insignificant while the parameters (γ) and (β) are significant at the 5 percent level of significance. Since the risk factor (δ) was also found to be statistically insignificant on the 5 percent level of significance, two other models were also simulated without taking the risk factor (δ) into consideration. These models include an AR(3) EGARCH(1,1) and an AR(1) EGARCH(1,1).

Both the AR(3) EGARCH(1,1) and the AR(1) EGARCH(1,1) models indicate a statistically significant Thursday effect in mean returns at the 5 percent level of significance in the South African All-Share index data. A value of 0.2220 was reported for the AR(3) EGARCH(1,1) and 0.2273 for the AR(1) EGARCH(1,1). For the AR(3) EGARCH(1,1), volatility in returns was found to be the highest on Fridays (0.0460) and lowest on Thursdays (0.0398). The AR(1) EGARCH(1,1) differed, however, from the previous models and reported that volatility was the highest on Mondays (0.0854) and the lowest on Thursdays (0.0782). In all of the above models, a mean returns effect was found on Thursdays, while a volatility effect (highest volatility in returns) was found on Fridays (with the exception of the AR(1) EGARCH(1,1) model for the latter). The descriptive statistics for the above models are set out in Tables 4.2 and 4.3 below.

TABLE 4.2   SUMMARY STATISTICS: EGARCH MODELS WITH RISK FACTOR

	AR(3) EGARCH(1,1) -M	AR(1) EGARCH(1,1) -M
Return Equation		
Constant	-0.0939	0.1008
	(0.0563)	(0.0815)
	[0.0952]	[0.2162]
Monday	0.1642	0.1620
	(0.0512)	(0.0850)
	[0.0013]*	[0.0566]
Tuesday	0.1168	0.1115
	(0.0482)	(0.0831)
	[0.0154]*	[0.1797]
Thursday	0.2218	0.2295
	(0.0428)	(0.0814)
	[<.0001]*	[0.0048]*
Friday	0.1742	0.1721
	(0.0651)	(0.0875)
	[0.0074] *	[0.0492]*
$Return_{t-1}$	-0.0886	-0.0967
	(0.0213)	(0.0284)
	[<.0001]*	[0.0007]*
$Return_{t-2}$	-0.0430	
	(0.0275)	
	[0.1173]	
$Return_{t-3}$	0.0830	
	(0.0275)	
	[0.0026]*	
Risk	0.0097	0.0113
	(0.0522)	(0.0488)
	[0.8528]	[0.8167]
Variance Equation		
φ_0	0.0028	0.0031
	(0.0033)	(0.0036)
	[0.3868]	[0.3890]
φ_1	0.1378	0.1396
	(0.0302)	(0.0311)
	[<.0001]*	[<.0001]*
γ	0.9846	0.9843
	(0.0081)	(0.0077)
	[<.0001]*	[<.0001]*
β	-0.4347	-0.4430
	(0.0983)	(0.0991)
	[<.0001]*	[<.0001]*
SBC	3572.29	3716.40
AIC	3546.65	3659.98

TABLE 4.3   SUMMARY STATISTICS: EGARCH MODELS WITHOUT RISK FACTOR

	AR(3) EGARCH(1,1)	AR(1) EGARCH(1,1)
Return Equation		
Constant	-0.0864	-0.0896
	(0.0340)	(0.0603)
	[0.0110]*	[0.1375]
Monday	0.1648	0.1617
	(0.0433)	(0.0854)
	[0.0001]*	[0.0582]
Tuesday	0.1202	0.1109
	(0.0446)	(0.0801)
	[0.0071]*	[0.1662]
Thursday	0.2220	0.2273
	(0.0398)	(0.0782)
	[<.0001]*	[0.0036]*
Friday	0.1748	0.1716
	(0.0460)	(0.0826)
	[0.0001]*	[0.0378]*
$Return_{t-1}$	-0.0888	-0.0961
	(0.0166)	(0.0281)
	[<.0001]*	[0.0006]*
$Return_{t-2}$	-0.0435	
	(0.0242)	
	[0.0721]	
$Return_{t-3}$	0.0825	
	(0.0221)	
	[0.0002]*	
Variance Equation		
φ_0	0.0030	0.0032
	(0.0032)	(0.0035)
	[0.3561]	[0.3659]
φ_1	0.1392	0.1405
	(0.0313)	(0.0315)
	[<.0001]*	[<.0001]*
γ	0.9851	0.9848
	(0.0081)	(0.0081)
	[<.0001]*	[<.0001]*
β	-0.4353	-0.4420
	(0.0981)	(0.0996)
	[<.0001]*	[<.0001]*
SBC	3714.50	3709.31
AIC	3652.95	3658.02

The p-values marked with * indicates those values that are significant at the 5 percent level of significance.

In order to decide on the best model, Akaike's information criterion (AIC) (Maddala, 2002:488) and Schwarz's Bayesian information criterion (SBC) were used (SAS Institute Inc., 2003). The AIC and the SBC are computed as follows:

$$AIC = -2\ln(L) + 2k,$$ (4.18)

$$SBC = -2\ln(L) + \ln(N)k,$$ (4.19)

where L is the value of the likelihood function evaluated at the parameter estimates, N is the number of observations, k is the number of estimated parameters.

The model with the lowest AIC and SBC values will be the one that expresses the patterns in the data best. The final model (based on amongst others, the AIC and SBC values) is used to test for the day-of-the-week effect in the South African All-Share index returns data.

According to the AIC and SBC measures the AR(3) EGARCH(1,1)-M predicts the patterns in the data the best, followed by the AR(1) EGARCH(1,1) and the AR(3) EGARCH(1,1).

After an elimination process based on these criteria, the final model decided upon was an AR(3) EGARCH(1,1)-M model (see Table 4.3 above). This model takes the form of:

$$R_t = \alpha_0 + \phi R_{t-3} + \alpha_2 M_t + \alpha_3 Tu_t + \alpha_4 Thu_t + \alpha_5 Fri_t + \delta \sigma_t + \varepsilon_t,$$ (4.20)

$$\varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \sigma_t^2\right),$$ (4.21)

$$\ln\left(\sigma_t^2\right) = \varphi_0 + \varphi_1 \left\{ \left| \varepsilon_{t-1}/\sigma_{t-1} \right| - \sqrt{2/\pi} \right\} + \gamma \varepsilon_{t-1}/\sigma_{t-1} + \beta \ln\left(\sigma_{t-1}^2\right),$$ (4.22)

where R_t is market return, M_t, Tu_t, Thu_t and Fri_t are dummy variables for Monday, Tuesday, Thursday, and Friday at time t; and ε_t represents the error term. For the daily dummy variables: $M_t = 1$, if day t is a Monday and 0 otherwise; $Tu_t = 1$, if day t is a

Tuesday and 0 otherwise; $Thu_t = 1$ if, day t is a Thursday and 0 otherwise; and $Fri_t = 1$ if, day t is a Friday and 0 otherwise.

The error term is assumed to follow a normal distribution, with Ω_{t-1} being the set of relevant information available at time t. If ε_t follows a normal distribution, it serves as evidence that autocorrelation has been removed from the data. The assumption of ε_t following a normal distribution was tested by making use of quantile-quantile (QQ) plots. QQ plots were fitted for both the error term ε_t and the standardised residuals, which are given by:

$$Std.\,res = \frac{\varepsilon_t}{\sqrt{\sigma^2}},$$

(4.23)

A QQ plot compares ordered values of a variable with quantiles of a specific theoretical distribution (normal, lognormal, exponential etc.). If, the data are from a specific theoretical distribution, the points on the QQ plot lie approximately on a straight line (SAS Institute Inc., 2003).

GRAPH 4.4   QUANTILE-QUANTILE PLOT OF THE ERROR TERMS IN THE AR(3) EGARCH(1,1)-M MODEL
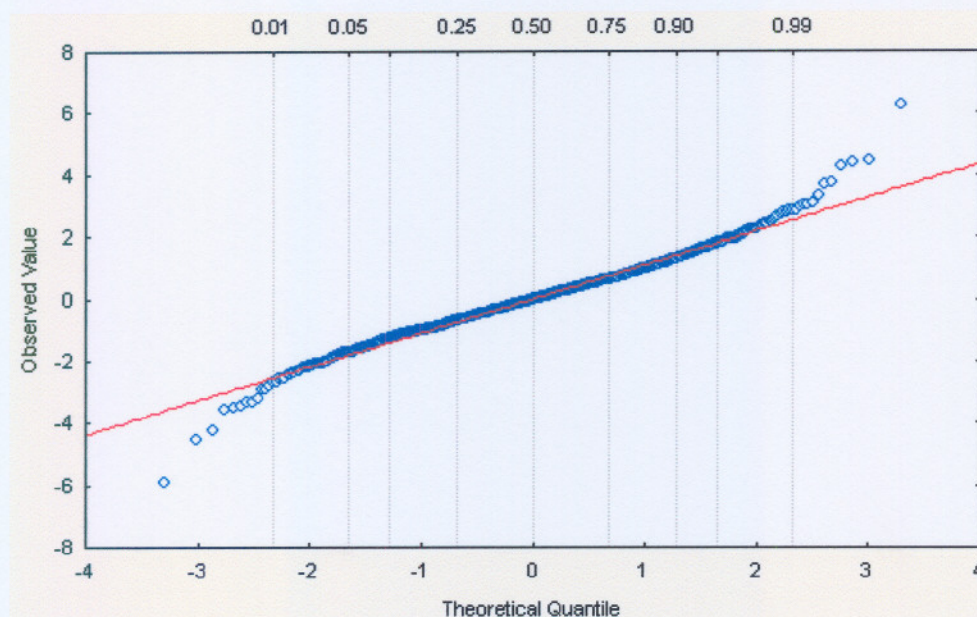
On the (horizontal) x-axis are the standard normal values (quantiles) corresponding to the same probability points as those of ε_t; on the (vertical) y-axis are the data values for those same probability points. Graph 4.4 above indicates that the error terms in the AR(3) EGARCH(1,1)-M model follow a normal distribution seeing as the observed distribution of ε_t closely matched the normal distribution.

GRAPH 4.5   QUANTILE-QUANTILE PLOT OF THE STANDARDISED ERROR TERMS IN THE AR(3) EGARCH(1,1)-M MODEL
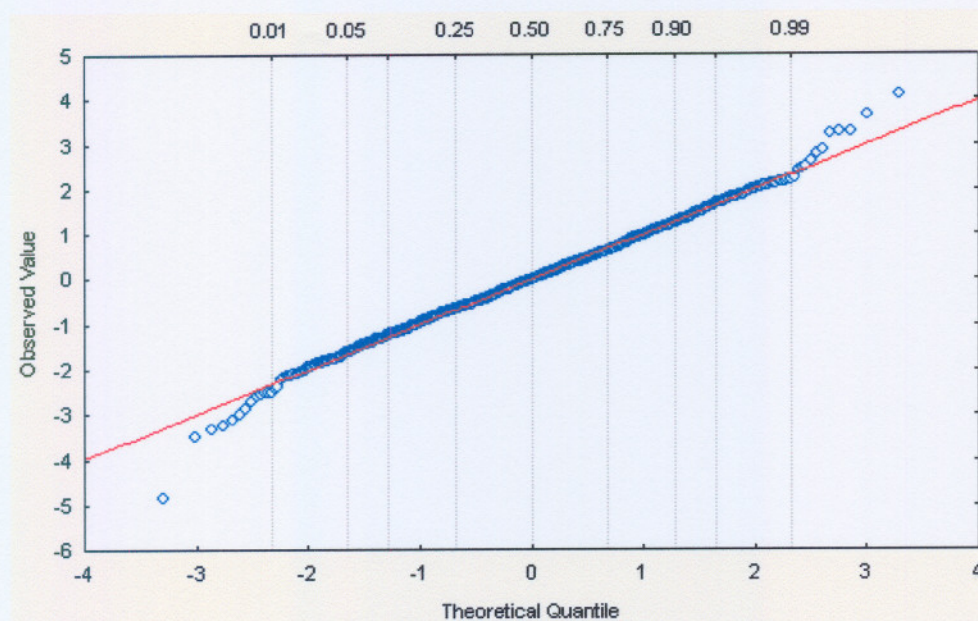
Graph 4.5 above, indicates that the standard error terms in the AR(3) EGARCH(1,1)-M model also follow a normal distribution.[27]

Equations 4.20 through 4.22 above remain the same as equations 4.15 through 4.17, and thus the parameters and their constraints remains the same too. The parameter (φ_1) measures the impact of innovations on conditional volatility at time t, while the parameter (γ) permits the asymmetric response of conditional variance to innovations of a differing sign. The parameter (β) is the autoregressive term on lagged conditional

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[27] The QQ plot results of the other EGARCH models can be viewed in the Statistical reports 1.9 – 1.14, see the annexure.

volatility, thus reflecting the weight given to previous period's conditional volatility in the conditional volatility at time t. For a full description of these parameters, refer to section 4.4.2.2 above.

It is to be noted that in testing the model any other day could be excluded, excepting Wednesday. As previously mentioned, this is necessary in order to avoid the dummy variable trap. Tables 4.4 and 4.5 detail the results (mean returns and volatility in returns) of successive applications of the model, excluding each of the other weekdays, respectively.

TABLE 4.4   MEAN RETURNS – RETURNS DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		-0.0436	-0.1554	**0.0605**	0.0129
Tuesday	0.0530		-0.1062	**0.1105**	0.0634
Wednesday	0.1642	0.1168		**0.2218**	0.1742
Thursday	-0.0495	-0.0968	-0.2099		**-0.0405**
Friday	-0.002931	-0.0476	-0.1614	**0.0541**	

TABLE 4.5   STANDARD ERROR – RETURNS DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		0.0608	**0.0644**	0.0457	0.0578
Tuesday	0.0770		0.0793	0.0726	**0.0830**
Wednesday	0.0512	0.0482		0.0428	**0.0651**
Thursday	0.0702	**0.0761**	0.0676		0.0651
Friday	0.0682	**0.0800**	0.0762	0.0692	

The highlighted values in tables 4.4 and 4.5 above indicate the highest value for the day of the week for both mean returns and volatility in returns values. The mean returns results remain the same (see column 5 of Table 4.4), irrespective of the day omitted. The results of the volatility in returns do, however, differ when other days are omitted.[28]

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[28] The results for the omission of the other days of the week can be viewed in the annexure. See Statistical Reports 1.9 – 1.12.

The reason for the difference in results may be explained by the relative importance of the other days in the week. Since Monday and Friday are the first and last days of the week (which can place psychological pressure on the market), they cannot be omitted. Thursdays too, can not be omitted due to the Futures contracts closing out on Thursdays every 3 months. Furthermore, the *p-values* for the majority of the dummy variables indicate that these models (in which, Monday, Tuesday, Thursday and Friday are omitted respectively) are not statistically significant.

The second method mentioned for testing for the day-of-the-week effect (see section 4.4.2.1), comprises of a model with all five days included as dummy variables. This method requires a restriction on the parameter estimates. This model is given by:

$$R_t = \alpha_0 + \alpha_1 M_t + \alpha_2 Tu_t + \alpha_3 Wed_t + \alpha_4 Thu_t + \alpha_5 Fri_t + \varepsilon_t, \qquad (4.24)$$

$$\varepsilon_t \,|\Omega_{t-1} \sim N\left(0, \sigma_t^2\right), \qquad (4.25)$$

$$\ln\left(\sigma_t^2\right) = \varphi_0 + \varphi_1 \left\{\left|\varepsilon_{t-1}/\sigma_{t-1}\right| - \sqrt{2/\pi}\right\} + \gamma \varepsilon_{t-1}/\sigma_{t-1} + \beta \ln\left(\sigma_{t-1}^2\right), \qquad (4.26)$$

with restriction : $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5 = 0$.

Note that the description of the dummy variables in equation 4.24 is the same as that of equation 4.13 (see section 4.4.2.1.). It must be further noted that the distribution of the error term follows a normal distribution (as in equation 4.21), with Ω_{t-1} the set of relevant information available at time t.

Table 4.6 below provides the descriptive statistics of the AR(3) EGARCH(1,1)-M model in which all five days are included. Table 4.6 reports the highest mean returns on Thursdays (0.0856), while Wednesdays have the lowest mean returns (-0.1316). The volatility in returns is the highest on Wednesdays (0.0526), and the lowest on Tuesdays (0.0519). It should be noted that the *p-values* for all the daily dummy variables, with the exception of Wednesday, are not statistically significant above the 5 percent level

of significance. Therefore, it is preferable to make use of the model that excludes Wednesdays from the equation.

TABLE 4.6   SUMMARY STATISTICS: AR(3) EGARCH(1,1)-M MODEL WITH RESTRICTED PARAMETER ESTIMATES

RETURN EQUATION		VARIANCE EQUATION	
Constant	0.0418	φ_0	0.0028
	(0.0600)		(0.0034)
	[0.4862]		[0.4089]
Monday	0.0278	φ_1	0.1384
	(0.0525)		(0.0310)
	[0.5968]		[<.0001]*
Tuesday	-0.0193	γ	0.9847
	(0.0519)		(0.0084)
	[0.7093]		[<.0001]*
Wednesday	-0.1316	β	-0.4347
	(0.0526)		(0.1019)
	[0.0123]*		[<.0001]*
Thursday	0.0856		
	(0.0521)		
	[0.1007]		
Friday	0.0376		
	(0.0524)		
	[0.4730]		
Return$_{t-1}$	-0.0881		
	(0.0287)		
	[0.0022]*		
Return$_{t-2}$	-0.0433		
	(0.0290)		
	[0.1356]		
Return$_{t-3}$	0.0828		
	(0.0288)		
	[0.0041]*		
Risk	0.0095		
	(0.0553)		
	[0.8642]		
SBC	3722.07		
AIC	3655.39		

4.4.2.4 Interpretation and implementation of Results

The AR(3) EGARCH(1,1)-M model confirms a Thursday effect in mean returns (highest returns), and a Friday effect in volatility patterns (highest volatility in returns)

relative to Wednesdays, for the South African All-share index returns data (see Table 4.3). This model further confirms that volatility is at its lowest level on Thursdays, and that mean returns is the lowest on Tuesdays, relative to Wednesdays.[29]

One possible reason, amongst other possible reasons, for the existence of the day-of-the-week effect in the South African market concerns the most central finding, that which implies the seasonal patterns on a Thursday. In the South African market, this Thursday effect in mean returns (and low volatility in returns) might be explained by the futures contracts close out dates.[30] The majority of the futures contracts traded on the Johannesburg Stock Exchange expires on the third Thursday of every third month (March, June, September and December). Moreover, there are a number of futures contracts that expire on every first Thursday of every other third month (February, May, August and November). It is only a small amount of futures contracts that expire on days other than Thursdays.

Therefore, liquidity ought to be high in the South African market on Thursdays. This assumption is confirmed by the All-share index trades on the JSE for the period of the study (JSE, 2005). For the period of the study the trading volume was the highest on Thursdays, 30.6 percent of the time in terms of value traded in ZAR rands, and 30.99 percent of the time in terms of the amount of stocks traded.

The value of stocks traded on Fridays indicates volatility with trading values being the highest 25.7 percent of the time, and the lowest 16.9 percent of the time. Therefore, the volumes traded on Fridays, confirms the volatility found by fitting the AR(3) EGARCH(1,1)-M model on the All-share index volumes and values data.

Tables 4.7 – 4.10 below provides the results (mean returns and volatility in returns) where each of the weekdays is excluded from the equation. Tables 4.7 – 4.10 confirm the mean returns effect on Thursdays, while no clear pattern of the volatility in returns

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[29] The full report for the AR(3) EGARCH(1,1)-M can be viewed in Statistical Report 1.5, see the annexure.

[30] A list of the most prominent futures contracts expiry dates can be viewed in the annexure. It is to be noted that all of these contracts, with the exception of two, expire on Thursdays.

can be found in the values and volumes data. In addition, these models' *p-values* indicate that these models are not statistically significant on the 5 percent level of significance.

TABLE 4.7   MEAN RETURNS – VALUES DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		0.4027	0.5432	**0.9077**	0.6873
Tuesday	-0.4087		0.1348	**0.5021**	0.2873
Wednesday	-0.5422	-0.1367		**0.3662**	0.1501
Thursday	-0.9109	-0.5059	-0.3739		**-0.2347**
Friday	-0.6841	-0.2847	-0.1436	**0.2208**	

TABLE 4.8   STANDARD ERROR – VALUES DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		0.0481	**0.0571**	0.0534	0.0559
Tuesday	0.0477		**0.0515**	0.0453	0.0508
Wednesday	**0.0524**	0.0424		0.0445	0.0481
Thursday	**0.0502**	0.0372	0.0402		0.0426
Friday	**0.0510**	0.0409	0.0390	0.0376	

TABLE 4.9   MEAN ESTIMATES – VOLUMES DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		0.1966	0.2763	**0.3427**	0.2876
Tuesday	-0.1980		0.0768	**0.1429**	0.0888
Wednesday	-0.2718	-0.0709		**0.0670**	0.0140
Thursday	-0.3351	-0.1361	-0.0646		**-0.0554**
Friday	-0.2848	-0.0838	-0.0086	**0.0562**	

TABLE 4.10   STANDARD ERROR – VOLUMES DATA

Day left out	Monday	Tuesday	Wednesday	Thursday	Friday
Monday		0.0369	0.0249	0.0230	**0.0387**
Tuesday	0.0218		0.0223	0.0232	**0.0241**
Wednesday	**0.0246**	0.0224		0.0233	0.0236
Thursday	**0.0242**	0.0237	0.0232		0.0239
Friday	0.0230	**0.0238**	0.0237	0.0225	

The above results have important implications for both prospective and current investors in the South African market. High volatility is generally accompanied by low trading volume, due to unwillingness of liquidity traders to trade in periods where the prices are more volatile (Foster & Viswanathan, 1990). The opposite is true for days on which mean returns are high and volatility in returns is low. In the South African market, Thursdays are thus to be considered 'good' (low risk) trading days, while Fridays are to be considered 'bad' (high risk) trading days. This information should be considered by hedge fund managers when they rebalance their portfolios (see steps 2 and 3 of the hedge fund risk management process in chapter 3).

Both the volatility effect on Fridays and mean returns effect on Thursdays hold significant implications for hedge fund managers in South Africa. Whenever hedge fund managers are forced to rebalance their portfolios, in order to keep to the hedge funds' mandate, they are exposed to market factors such as the day-of the-week effect. This day-of-the-week effect in the South African market impacts on hedge fund managers both positively and negatively.

The Friday volatility effect will pose a definite risk for the hedge fund manager that intends to execute his trades on a Friday. This risk manifests in the possible inability of the hedge fund manager to close out his position in the market before the price of the instrument changes adversely. There is also the possibility that the hedge fund manager might open a position in the market shortly before its price changes. Events such as these might ultimately be very costly to the hedge fund and therefore its investors.

In contrast to this, the Thursday mean returns effect provides the hedge fund manager with an opportunity to take advantage of favourable market conditions. Days on which mean returns are high and volatility in returns is low, hedge fund mangers need not be concerned that prices will move adversely in a short period of time. Hedge fund managers should be able to exploit these favourable conditions so as to earn greater returns on their portfolios, by closing out positions before their value deteriorates and opening positions before their value appreciates.

In summary, hedge fund managers should avoid rebalancing their portfolios on Fridays. They should rather execute their trades on Thursdays, when mean returns are high and volatility in returns low.

4.4.3 Conclusion

In following Chang et al. (1993) and Gibbons and Hess (1981) a basic OLS model was chosen to test for a day-of-the-week effect in the South African data. However, OLS models have various weaknesses, the foremost being that it does not account for autocorrelation in time series data. In following Berument and Kiymaz (2001:3) the issue of autocorrelation was addressed by inserting lags in the return equation. In addition to showing evidence of autocorrelation, the data also showed evidence of heteroskedasticity. To address the issue of heteroskedasticity, Nelson (1991) and Ogum et al. (2002) were followed and four GARCH models were tested for their suitability for testing for a day-of-the-week effect in volatility in the South African All-Share index returns. By making use of Akaike's information criterion (Maddala, 2002:488) and Schwarz's Bayesian information criterion (SAS Institute Inc., 2003) the best model was shown to be the AR(3) EGARCH(1,1)-M.

The AR(3) EGARCH(1,1)-M model was fitted on South African All-share index returns data and revealed two day-of-the-week effects in the South African market. On Thursdays, mean returns were found to be the highest while volatility in returns was found to be the lowest. Furthermore, mean returns were found to be the lowest on Tuesdays and volatility in returns was found to be the highest on Fridays.

Both the Thursday effect (highest mean returns and lowest volatility in returns) and Friday effect (highest volatility in returns) have significant implications for hedge fund mangers in South Africa. It thus follows that hedge fund managers would be well advised to avoid rebalancing their portfolios on Fridays and rather execute their trades on Thursdays, when volatility in returns is low and mean returns are high.

Chapter 5 concludes this dissertation with an overview of the hedge fund industry, the risk management process in hedge funds and the day-of-the-week effect. A brief summary of the findings of the study of the day-of-the-week effect and its implications for hedge fund managers follows thereafter. Finally, some suggestions for future study are put forward for consideration.

CHAPTER 5

The Day-of-the-Week Effect and Hedge Funds

We don't have to be smarter than the rest; we have to be more disciplined than the rest.

Warren Buffett

(Hagstrom, 2005)

5.1 Introduction

Chapter 5 commences with a brief review of the relevant information discussed in the previous chapters. Firstly, a brief overview is given of hedge funds, their history, investment strategies and the current status of the hedge fund industry in South Africa. Thereafter an overview of the hedge fund management is given, followed by a short discussion about the day-of-the-week effect as a specific risk for hedge fund managers follows. Some suggestions for further study are also made.

5.2 Study Review: Hedge Funds

In chapter 2 it was shown that hedge funds have been in existence for more than 5 decades, and have survived several financial crises. The hedge fund industry has grown from a meagre 200 funds in 1968 to the current figure of approximately 8 000 funds.

As with traditional investments, a major source of risk for hedge funds is market risk, that is, the risk that the value of a fund's assets declines because of adverse movements in market variables, such as interest rates, exchange rates or security prices. This risk can be increased by leverage, or reduced by hedging strategies. Hedge funds are a class of investment vehicles that aim to generate market independent returns by utilising a range of non-traditional investment techniques, and by investing across a range of markets. These investment vehicles are known for their alternative investment

techniques, such as short selling, economic (debt) leverage and trade in leveraged financial instruments etc. Furthermore, hedge fund managers are allowed broader mandates than traditional funds, which give managers more flexibility to shift their strategy to achieve their risk and return profile.

5.3 Study Review: Risk Management in Hedge Funds

Chapter 3 explored various risk measurement tools and reported on the risk management process within the average hedge fund. Due to the nature of hedge funds' investment strategies, hedge fund managers follow a strict risk management process. Even though hedge fund managers are allowed broader mandates, they are still required to adhere to these mandates. These mandates are constantly in play to ensure that the ideal risk profile is maintained. During the risk management process, the compliance department will typically receive a risk report that indicates whether or not the mandate was breached.

In order to prevent a breach of mandate, hedge fund managers rebalance their portfolios on a regular basis. When they rebalance their portfolios, hedge fund managers are exposed to various market risks such as adverse volatility patterns. In the case of a breach in the mandate, the hedge fund manager will be held responsible, and is bound to ensure that the breach is corrected as soon as possible.[31]

5.4 Study Review: The Day-of-the-Week Effect

Chapter 4 reports on various studies on the day-of-the-week effect in the literature and further explore this phenomenon in the South African market. The day-of-the-week effect has been investigated and documented since M.F.M Osborne discovered a cyclical pattern in volatility in the stock prices on the NYSE in 1959. After this discovery, many studies have been undertaken, covering a variety of financial instruments and a series of countries. It was found that the volatility and mean returns

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[31] See steps 4 through 8 in section 3.3 p 54 – 55 for the full explanation of this part of the risk management process within the typical hedge fund.

patterns differ between the various financial instruments and for the countries modelled.

The studies of Gibbons and Hess (1981), and Keim and Stambaugh (1984) amongst others, confirmed that the average return on Mondays is considerably lower than the average return during the other days of the week, for U.S. stock returns data.

Berument and Kiymaz (2001) also investigated the day-of-the-week effect by making use of S & P 500 stock index data, and they drew distinctions between patterns in mean returns and volatility in returns. In their study, they describe returns as the logarithm of the daily difference in end-of-the-day index closing prices. They found that the day of the week effect is present in both volatility and return equations. While the highest and lowest returns were observed for Wednesdays and Mondays, the highest and the lowest volatilities were observed for Friday and Wednesdays, respectively.

The results of the study for the South African data, performed in this dissertation, show that the highest returns is observed on Thursdays, while the lowest return is observed on Tuesdays. It was also found that Fridays have the highest volatility in returns, and that Thursdays have the lowest volatility in returns. These results are confirmed by the evidence of the trading volumes on the All-share index data for the period of the study.

It is to be noted that the results for the South African data resemble other studies in that, the day with the highest mean returns has the lowest volatility in returns.

5.5 Conclusion

The aims of this dissertation were twofold. First, to determine the existence of the day-of-the-week effect (a specific market anomaly) in the South African market by making use of various volatility measurement tools. This was accomplished by testing for seasonal patterns in mean returns and volatility in returns in the South African market. The results were obtained by fitting an AR(3) EGARCH(1,1)-M model on the South African All-Share index returns data, for the period of 30 May 2000 to 27 May 2005. It

was found that Thursdays have the highest mean returns and the lowest volatility in returns. The results further indicated that Fridays have the highest volatility in returns. These findings correlate with the evidence found in the trading volumes of the All-share index data. The volumes traded on the All-share index shows that trading activity on Thursdays is the highest for both volumes traded and values traded. The abovementioned results, found in this study, hold serious implications for hedge fund managers.

Although hedge funds are renowned for giving their investors large returns on their investments, these investment vehicles are also known, however, for several negative traits, such as taking high leveraged, and sometimes, risky positions in the market. For hedge fund managers to be in the position to return their investors' money with interest, they need to be aware of all the risks inherent in their investment activities.

For a rational financial decision maker, returns constitute only one part of the decision-making process. Another aspect to be taken into account when one makes investment decisions is the volatility of returns (risk). It is important to know whether there are variations in volatility of returns by the day of the week and whether a high (low) return is associated with a correspondingly high (low) volatility for a given day.

The second aim of this dissertation is to better understand and describe the impact of the day-of-the-week effect on hedge fund managers in the South African market. The day-of-the-week effect thus becomes another risk for hedge fund managers to manage as part of the hedge fund risk management process. As previously mentioned, the hedge fund manager is bound to keep to the hedge fund's mandate and therefore rebalances his portfolio on a regular basis. During this rebalancing process, the hedge fund manager will typically open new positions, close out some old positions, enlarge some positions and reduce other positions.

It is during this rebalancing process that the hedge fund might be exposed to situations of unnecessarily high market volatility. Should a South African hedge fund manager like to rebalance his portfolio of South African stocks, he is advised to do it on a day

that has the lowest volatility in returns. It follows that the hedge fund manager runs the risk of being unable to rebalance his portfolio quickly enough to avoid losses caused by having the wrong positions in the market at that time. The opposite is also true: the hedge fund manager will profit on days where there is low volatility and high mean returns in the market.

The results of the empirical study in chapter 4 indicate that Thursdays have the highest mean returns and the lowest volatility in returns, while Fridays have the highest volatility in returns. Hedge fund managers are thus advised to rebalance their portfolios on Thursdays when volatility in returns is low and liquidity is high. Fridays are to be avoided because of the high volatility in returns on these days.

5.6 Suggestions for Further Study

The scope of this dissertation is vast, and therefore allows for various other studies. Some suggestions are the testing for seasonal patterns in different financial instruments, specific portfolios and financial assets; and the providing of other reasons for the existence of the mean returns and volatility effects in the South African market.

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ANNEXURE

STATISTICAL REPORT 1.1

AUTOCORRELATION TEST ON OLS MODEL BEFORE LAGS

Durbin-Watson Statistics

Order	DW	Pr < DW	Pr > DW
1	1.7755	<.0001	1.0000
2	1.9333	0.1314	0.8686
3	2.1097	0.9782	0.0218
4	2.0413	0.7962	0.2038
5	2.0899	0.9466	0.0534
6	1.9943	0.5272	0.4728

STATISTICAL REPORT 1.2

ARCH TEST FOR HETEROSKEDASTICITY BEFORE APPLYING AR(3)EGARCH(1,1)-M

Q and LM Tests for ARCH Disturbances

Order	Q	Pr > Q	LM	Pr > LM
1	21.8421	<.0001	21.8528	<.0001
2	41.7525	<.0001	36.9246	<.0001
3	66.8908	<.0001	53.1099	<.0001
4	88.5973	<.0001	63.5098	<.0001
5	92.9166	<.0001	63.5935	<.0001
6	103.8318	<.0001	66.6854	<.0001
7	132.5444	<.0001	81.1980	<.0001
8	147.4554	<.0001	85.0475	<.0001
9	156.0093	<.0001	85.8390	<.0001
10	160.7518	<.0001	85.8479	<.0001
11	163.0418	<.0001	86.1328	<.0001
12	164.0908	<.0001	86.2994	<.0001

STATISTICAL REPORT 1.3

ESTIMATION OF AUTOREGRESSIVE LAGS

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.2328	1.000000	| |******************|
1	0.1383	0.112160	| |** |
2	0.0399	0.032376	| |* |
3	-0.0699	-0.056669	| *| |
4	-0.0278	-0.022569	| | |
5	-0.0589	-0.047767	| *| |
6	-0.00104	-0.000845	| | |

Backward Elimination of Autoregressive Terms

Lag	Estimate	t Value	Pr > |t|
4	0.005814	0.20	0.8389
6	-0.006304	-0.22	0.8245
2	-0.024527	-0.86	0.3903
5	0.043307	1.54	0.1244

Estimates of Autoregressive Parameters

Lag	Coefficient	Standard Error	t Value
1	-0.114115	0.028170	-4.05
3	0.060363	0.028170	2.14

STATISTICAL REPORT 1.4

**ARCH TEST FOR HETEROSKEDASTICITY AFTER APPLYING AR(3)
EGARCH(1,1)-M**

Q and LM Tests for ARCH Disturbances

Order	Q	Pr > Q	LM	Pr > LM
1	0.8792	0.3484	0.8955	0.3440
2	0.9559	0.6201	0.9762	0.6138
3	4.8583	0.1825	4.9547	0.1751
4	13.0513	0.0110	12.5969	0.0134
5	13.4056	0.0199	13.1076	0.0224
6	13.5729	0.0348	13.3073	0.0384
7	15.6779	0.0282	14.6538	0.0407
8	16.2238	0.0393	15.5668	0.0490
9	17.0552	0.0479	16.0484	0.0659
10	17.7955	0.0585	16.7191	0.0808
11	17.9327	0.0832	16.7550	0.1153
12	19.1661	0.0846	17.4527	0.1333

STATISTICAL REPORT 1.5

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1)-M MODEL)

Exponential GARCH Estimates

SSE	1514.85663	Observations	1248
MSE	1.21383	Uncond Var	
Log Likelihood	- 1814.4614	Total R-Square	0.0200
SBC	3721.6036	AIC	3654.92274
Normality Test	33.8586	Pr > ChiSq	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	- 0.0939	0.0563	- 1.67	0.0952	
Monday	1	0.1642	0.0512	3.21	0.0013	Monday
Tuesday	1	0.1168	0.0482	2.42	0.0154	Tuesday
Thursday	1	0.2218	0.0428	5.18	<.0001	Thursday
Friday	1	0.1742	0.0651	2.68	0.0074	Friday
AR1	1	- 0.0886	0.0213	- 4.16	<.0001	
AR2	1	- 0.0430	0.0275	- 1.57	0.1173	
AR3	1	0.0830	0.0275	3.02	0.0026	
EARCH0	1	0.0028	0.0033	0.87	0.3868	
EARCH1	1	0.1387	0.0302	4.59	<.0001	
EGARCH1	1	0.9846	0.0081	121.52	<.0001	
THETA	1	- 0.4347	0.0983	- 4.42	<.0001	
DELTA	1	0.0097	0.0522	0.19	0.8528	

OTHER MODELS FITTED

STATISTICAL REPORT 1.6

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1) MODEL)

Exponential GARCH Estimates

SSE	1515.47007	Observations	1248
MSE	1.21432	Uncond Var	
Log Likelihood	- 1814.4755	Total R-Square	0.0159
SBC	3714.50264	AIC	3652.95107
Normality Test	33.6024	Pr > ChiSq	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	- 0.0864	0.0340	- 2.54	0.0110	
Monday	1	0.1648	0.0433	3.81	0.0001	Monday
Tuesday	1	0.1202	0.0446	2.69	0.0071	Tuesday
Thursday	1	0.2220	0.0398	5.57	<.0001	Thursday
Friday	1	0.1748	0.0460	3.80	0.0001	Friday
AR1	1	- 0.0888	0.0166	- 5.36	<.0001	
AR2	1	- 0.0435	0.0242	- 1.80	0.0721	
AR3	1	0.0825	0.0221	3.73	0.0002	
EARCH0	1	0.002950	0.003197	0.92	0.3561	
EARCH1	1	0.1392	0.0313	4.45	<.0001	
EGARCH1	1	0.9851	0.008083	121.87	<.0001	
THETA	1	- 0.4353	0.0981	- 4.44	<.0001	

STATISTICAL REPORT 1.7

STATISTICAL ESTIMATES (AR(1) EGARCH(1,1)-M MODEL)

Exponential GARCH Estimates

SSE	1520.36514	Observations	1248	
MSE	1.21824	Uncond Var		
Log Likelihood	- 1818.9904	Total R-Square	0.0165	
SBC	3716.40316	AIC	3659.98089	
Normality Test	35.4714	Pr > ChiSq	<.0001	

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	- 0.1008	0.0815	- 1.24	0.2162	
Monday	1	0.1620	0.0850	1.91	0.0566	Monday
Tuesday	1	0.1115	0.0831	1.34	0.1797	Tuesday
Thursday	1	0.2295	0.0814	2.82	0.0048	Thursday
Friday	1	0.1721	0.0875	1.97	0.0492	Friday
AR1	1	- 0.0967	0.0284	- 3.41	0.0007	
EARCH0	1	0.003070	0.003563	0.86	0.3890	
EARCH1	1	0.1396	0.0311	4.49	<.0001	
EGARCH1	1	0.9843	0.007694	127.93	<.0001	
THETA	1	- 0.4430	0.0991	- 4.47	<.0001	
DELTA	1	0.0113	0.0488	0.23	0.8167	

STATISTICAL REPORT 1.8

STATISTICAL ESTIMATES (AR(1) EGARCH(1,1) MODEL)

Exponential GARCH Estimates

SSE	1521.2527	Observations	1248
MSE	1.21895	Uncond Var	
Log Likelihood	- 1819.0087	Total R-Square	0.0159
SBC	3709.31035	AIC	3658.01737
Normality Test	35.0601	Pr > ChiSq	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	- 0.0896	0.0603	-1.49	0.1375	
Monday	1	0.1617	0.0854	1.89	0.0582	Monday
Tuesday	1	0.1109	0.0801	1.38	0.1662	Tuesday
Thursday	1	0.2273	0.0782	2.91	0.0036	Thursday
Friday	1	0.1716	0.0826	2.08	0.0378	Friday
AR1	1	- 0.0961	0.0281	-3.42	0.0006	
EARCH0	1	0.003169	0.003505	0.90	0.3659	
EARCH1	1	0.1405	0.0315	4.46	<.0001	
EGARCH1	1	0.9848	0.0081	121.70	<.0001	
THETA	1	- 0.4420	0.0996	-4.44	<.0001	

AR(3) EGARCH(1,1)-M MODELS FITTED WHILE LEAVING OUT DIFFERENT DAYS OF THE WEEK AS DUMMY VARIABLES

STATISTICAL REPORT 1.9

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1)-M MODEL) WITH NO MONDAY

Exponential GARCH Estimates

SSE	1515.42715	Observations	1248
MSE	1.21428	Uncond Var	
Log Likelihood	-1814.7486	Total R-Square	0.0197
SBC	3722.17799	AIC	3655.49712
Normality Test	33.6455	Pr > ChiSq	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.0683	0.0451	1.51	0.1301	
Tuesday	1	- 0.0436	0.0608	- 0.72	0.4735	Tuesday
Wednesday	1	- 0.1554	0.0644	- 2.41	0.0159	Wednesday
Thursday	1	0.0605	0.0457	1.32	0.1858	Thursday
Friday	1	0.0129	0.0578	0.22	0.8234	Friday
AR1	1	- 0.0882	0.0209	- 4.22	<.0001	
AR2	1	- 0.0429	0.0254	- 1.69	0.0914	
AR3	1	0.0835	0.0249	3.35	0.0008	
EARCH0	1	0.002806	0.002923	0.96	0.3371	
EARCH1	1	0.1386	0.0182	7.63	<.0001	
EGARCH1	1	0.9847	0.007103	138.64	<.0001	
THETA	1	- 0.4339	0.0706	- 6.14	<.0001	
DELTA	1	0.008624	0.0511	0.17	0.8659	

STATISTICAL REPORT 1.10

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1)-M MODEL) WITH NO TUESDAY

Exponential GARCH Estimates

SSE	1515.27413	Observations	1248
MSE	1.21416	Uncond Var	
Log Likelihood	- 1814.6532	Total R-Square	0.0198
SBC	3721.98731	AIC	3655.30644
Normality Test	34.0325	Pr > ChiSq	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.0173	0.0803	0.22	0.8295	
Monday	1	0.0530	0.0770	0.69	0.4914	Monday
Wednesday	1	- 0.1062	0.0793	- 1.34	0.1803	Wednesday
Thursday	1	0.1105	0.0726	1.52	0.1279	Thursday
Friday	1	0.0634	0.0830	0.76	0.4446	Friday
AR1	1	- 0.0884	0.0199	- 4.44	<.0001	
AR2	1	- 0.0433	0.0275	- 1.57	0.1159	
AR3	1	0.0829	0.0286	2.90	0.0038	
EARCH0	1	0.002837	0.003534	0.80	0.4222	
EARCH1	1	0.1385	0.0315	4.39	<.0001	
EGARCH1	1	0.9847	0.008654	113.78	<.0001	
THETA	1	- 0.4350	0.1023	- 4.25	<.0001	
DELTA	1	0.009646	0.0482	0.20	0.8414	

STATISTICAL REPORT 1.11

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1)-M MODEL) WITH NO THURSDAY

Exponential GARCH Estimates

SSE	1515.4014	Observations	1248	
MSE	1.21426	Uncond Var		
Log Likelihood	- 1814.8693	Total R-Square	0.0197	
SBC	3722.41952	AIC	3655.73865	
Normality Test	33.8573	Pr > ChiSq	<.0001	

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.1213	0.0696	1.74	0.0812	
Monday	1	- 0.0495	0.0702	- 0.70	0.4811	Monday
Tuesday	1	- 0.0968	0.0761	- 1.27	0.2031	Tuesday
Wednesday	1	- 0.2099	0.0676	- 3.10	0.0019	Wednesday
Friday	1	- 0.0405	0.0651	- 0.62	0.5345	Friday
AR1	1	- 0.0879	0.0279	- 3.15	0.0016	
AR2	1	- 0.0435	0.0294	- 1.48	0.1394	
AR3	1	0.0828	0.0277	2.99	0.0027	
EARCH0	1	0.002852	0.003258	0.88	0.3813	
EARCH1	1	0.1383	0.0288	4.79	<.0001	
EGARCH1	1	0.9847	0.007971	123.53	<.0001	
THETA	1	- 0.4339	0.0934	- 4.65	<.0001	
DELTA	1	0.009291	0.0512	0.18	0.8561	

STATISTICAL REPORT 1.12

STATISTICAL ESTIMATES (AR(3) EGARCH(1,1)-M MODEL) WITH NO FRIDAY

Exponential GARCH Estimates

SSE	1515.13604	Observations	1248	
MSE	1.21405	Uncond Var		
Log Likelihood	- 1814.7659	Total R-Square	0.0199	
SBC	3722.21261	AIC	3655.53174	
Normality Test	33.8129	Pr > ChiSq	<.0001	

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.0739	0.0805	0.92	0.3582	
Monday	1	- 0.002931	0.0682	- 0.04	0.9657	Monday
Tuesday	1	- 0.0476	0.0800	- 0.59	0.5519	Tuesday
Wednesday	1	- 0.1614	0.0762	- 2.12	0.0341	Wednesday
Thursday	1	0.0541	0.0692	0.78	0.4341	Thursday
AR1	1	- 0.0881	0.0228	- 3.86	0.0001	
AR2	1	- 0.0431	0.0270	- 1.59	0.1109	
AR3	1	0.0829	0.0267	3.10	0.0019	
EARCH0	1	0.002823	0.003630	0.78	0.4368	
EARCH1	1	0.1385	0.0348	3.98	<.0001	
EGARCH1	1	0.9846	0.008380	117.50	<.0001	
THETA	1	- 0.4342	0.0963	- 4.51	<.0001	
DELTA	1	0.009057	0.0481	0.19	0.8506	

QUANTILE-QUANTILE PLOTS

STATISTICAL REPORT 1.13

QUANTILE-QUANTILE PLOT OF ERROR TERMS (AR(3) EGARCH(1,1) MODEL)
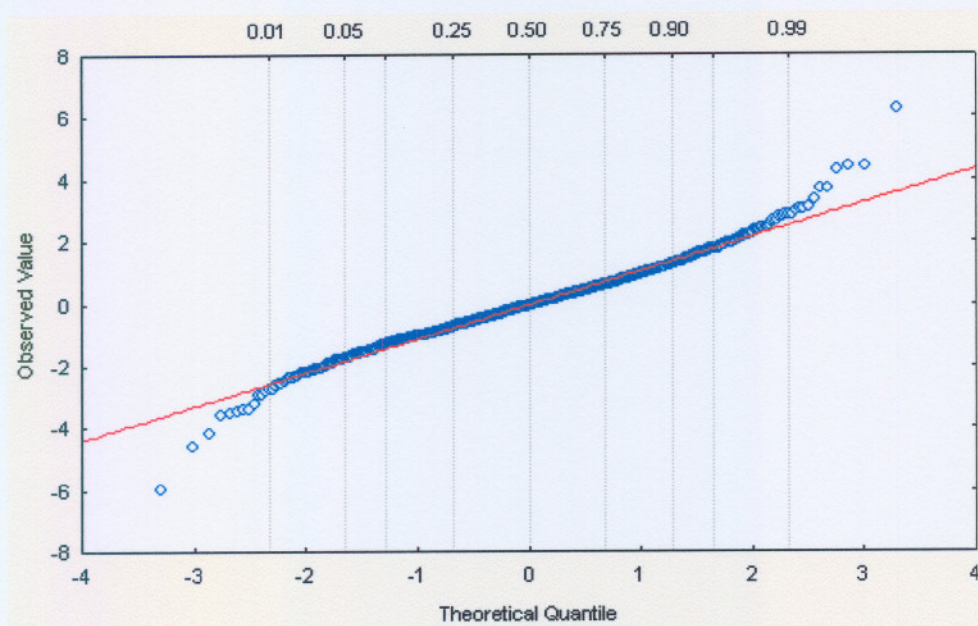
STATISTICAL REPORT 1.14

QUANTILE-QUANTILE PLOT OF THE STANDARDISED ERROR TERMS (AR(3) EGARCH(1,1) MODEL)
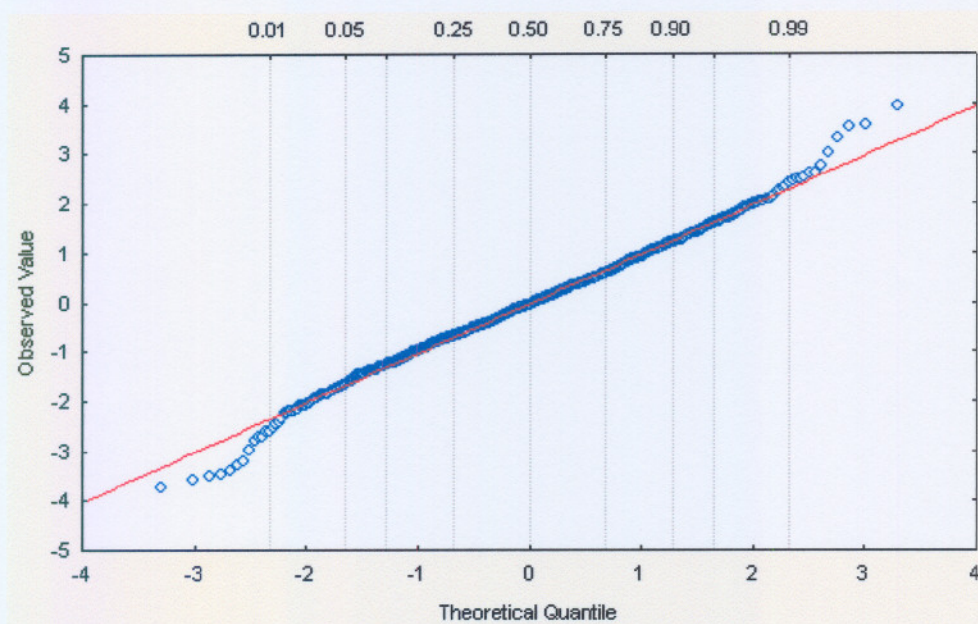
STATISTICAL REPORT 1.15

QUANTILE-QUANTILE PLOT OF ERROR TERMS (AR(1) EGARCH(1,1)-M MODEL)
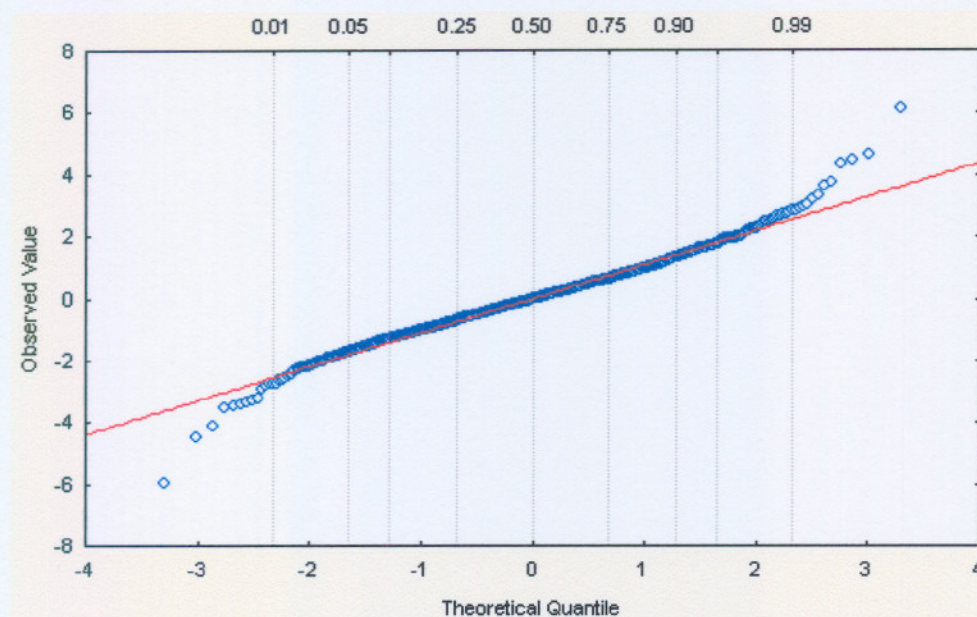
STATISTICAL REPORT 1.16

QUANTILE-QUANTILE PLOT OF THE STANDARDISED ERROR TERMS (AR(1) EGARCH(1,1)-M MODEL)
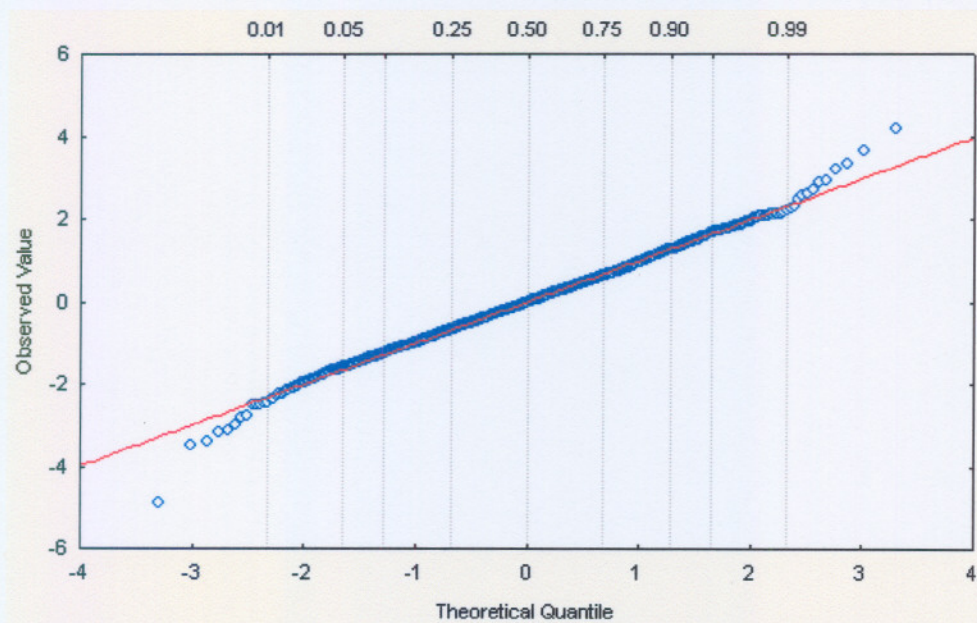
STATISTICAL REPORT 1.17

QUANTILE-QUANTILE PLOT OF ERROR TERMS (AR(1) EGARCH(1,1) MODEL)
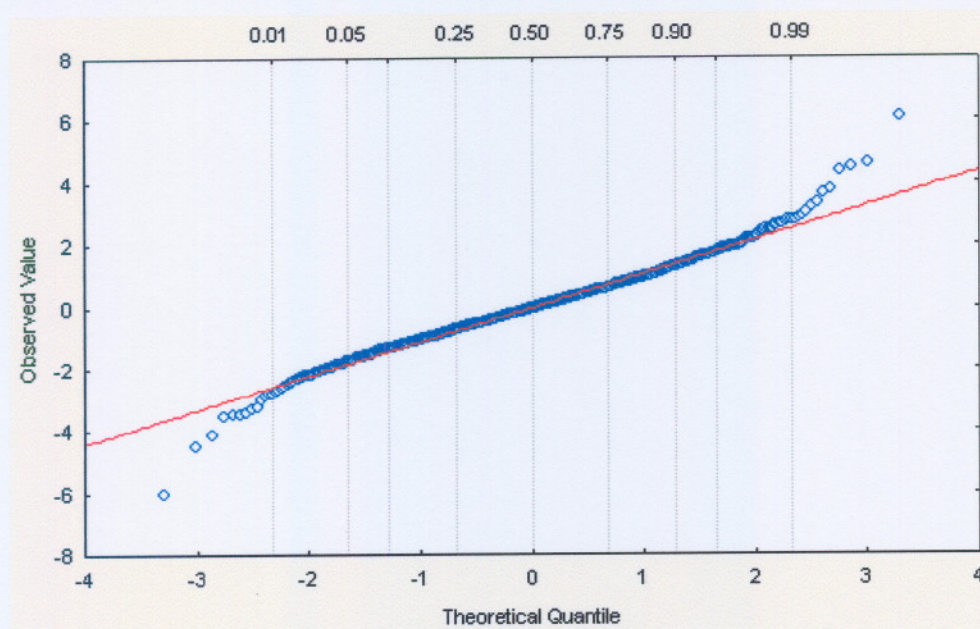
STATISTICAL REPORT 1.18

QUANTILE-QUANTILE PLOT OF THE STANDARDISED ERROR TERMS (AR(1) EGARCH(1,1) MODEL)
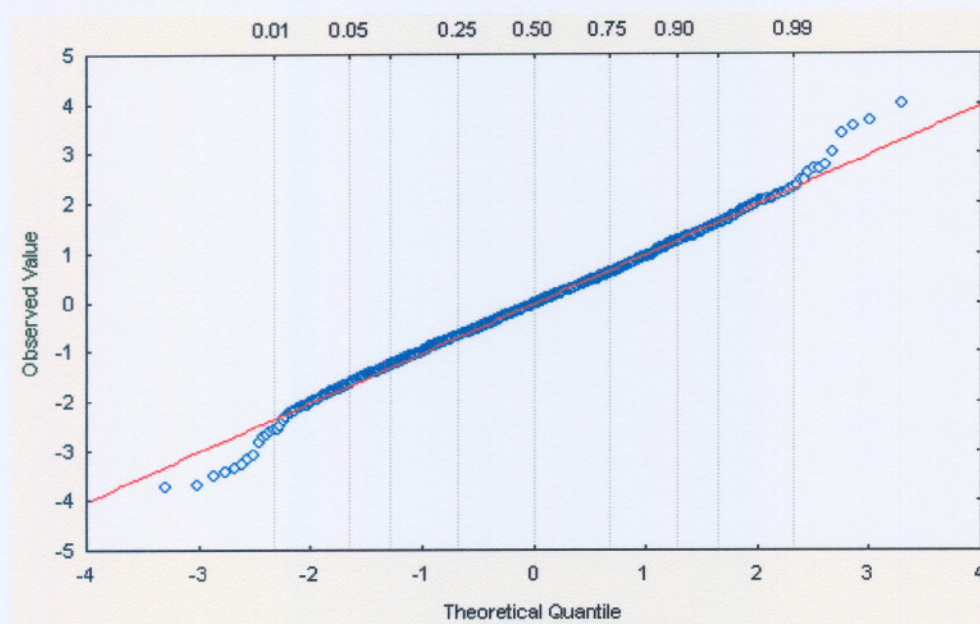
STATISTICAL REPORT 1.19

SOUTH AFRICAN FUTURES CONTRACT EXPIRY DATES

Futures Contract	FTSE/JSE Top 40 Index Future	FTSE/JSE INDI 25 Index Future	FTSE/JSE FINI 15 Index Future	FTSE/JSE FNDI 30 Index Future	FTSE/JSE Gold Mining Index Future
Code	ALSI	INDI	FINI	FNDI	GLDX
Underlying Instrument	FTSE/JSE Top 40 Index Future	FTSE/JSE INDI 25 Index Future	FTSE/JSE FINI 15 Index Future	FTSE/JSE FNDI 30 Index Future	FTSE/JSE Gold Mining Index Future
Contract Size	R10 x Index Level	R10 x Index Level	R10 x Index Level	R10 x Index Level	R10 x Index Level
Expiry Dates & Times	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)
Quotations	Index Level (no decimal points)	Index Level (no decimal points)	Index Level (no decimal points)	Index Level (no decimal points)	Index Level (no decimal points)
Minimum Price Movement	One Index Point (R10)	One Index Point (R10)	One Index Point (R10)	One Index Point (R10)	One Index Point (R10)
Expiry Valuation Method	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.
Settlement Method	Cash Settled	Cash Settled	Cash Settled	Cash Settled	Cash Settled
Clearing House Fees	Futures R 1.33 Options R 0.67	Futures R 1.00 Options R 0.50	Futures R 0.50 Options R 0.25	Futures R 1.33 Options R 0.67	Futures R 0.33 Options R 0.17

Futures Contract	FTSE/JSE RESI 20 Index Future	FTSE/JSE Capped Top 40 Index Future	FTSE/JSE Shareholder Weighted Top 40 Index Future	FTSE/JSE SA Listed Property Index	Kruger Rand Future
Code	RESI	CTOP	DTOP	SAPI	KGRD
Underlying Instrument	FTSE/JSE RESI 20 Index Future	FTSE/JSE Capped Top 40 Index Future	FTSE/JSE Shareholder Weighted Top 40 Index Future	FTSE/JSE SA Listed Property Index	Kruger Rand
Contract Size	R10 x Index Level	R10 x Index Level	R10 x Index Level	R10 x Index Level	1 Kruger Rand
Expiry Dates & Times	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	15h40 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	17h00 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)
Quotations	Index Level (no decimal points)	Index Level (no decimal points)	Index Level (no decimal points)	Index Level to Two Decimal points	In whole rands to 2 decimals
Minimum Price Movement	One Index Point (R10)	One Index Point (R10)	One Index Point (R10)	0.01	0.01
Expiry Valuation Method	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Arithmetic average of the index taken every 60 seconds (100 iteration), between 14h01 and 15h40, as calculated by the JSE Securities Exchange.	Official closing price as determined by the JSE Securities Exchange
Settlement Method	Cash Settled	Cash Settled	Cash Settled	Cash Settled	Physically settled
Clearing House Fees	Futures R 3.17 Options R 1.58	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 0.06 Options R 0.03	Futures R 2.50 Options R 1.75

Futures Contract	Kruger Rand Tenth Future	RSA R152 Loan Stock 12% 2005	RSA R153 Loan Stock 13% 2010	RSA R157 Loan Stock 13.5% 2015	RSA R186 Loan Stock 10.5% 2026
Code	KRTT	R152	R153	R157	R186
Underlying Instrument	Kruger Rand Tenth	RSA R152 Loan Stock 12% 2005	RSA R153 Loan Stock 13% 2010	RSA R157 Loan Stock 13.5% 2015	RSA R186 Loan Stock 10.5% 2026
Contract Size	1 Kruger Rand Tenth	R 1,000,000 nominal	R 1,000,000 nominal	R 1,000,000 nominal	R 1,000,000 nominal
Expiry Dates & Times	17h00 on 3rd Thursday of Mar, Jun, Sep & Dec. (or previous business day if a public holiday)	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)
Quotations	In whole rands to 2 decimals	Yield to maturity to 4 decimal places	Yield to maturity to 4 decimal places	Yield to maturity to 4 decimal places	Yield to maturity to 4 decimal places
Minimum Price Movement	0.01	One twentieth of a point (0.0005%)	One twentieth of a point (0.0005%)	One twentieth of a point (0.0005%)	One twentieth of a point (0.0005%)
Expiry Valuation Method	Official closing price as determined by the JSE Securities Exchange	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry
Settlement Method	Physically settled	Physically settled	Physically settled	Physically settled	Physically settled
Clearing House Fees	Futures R 0.25 Options R 0.18	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50

Futures Contract	RSA R194 Loan Stock 10% 2008	RSA R201 Loan Stock 8.75% 2014	BEASSA Total Return Bond Index	Rand Dollar	Three Month JIBAR interest rate
Code	R194	R201	GOVI	RNDD	JBAR
Underlying Instrument	RSA R194 Loan Stock 10% 2008	RSA R201 Loan Stock 8.75% 2014	BEASSA Total Return Government Bond Index	Rate of Exchange between S A Rand and U S Dollars	The three month Johannesburg Inter-Bank agreed rate (JIBAR)
Contract Size	R 1,000,000 nominal	R 1,000,000 nominal	The index level multiplied by R10,000.00 (If the index level is 104.921, contract size would be R 1,049,210.00	$ 100,000 nominal	R 1,000,000 nominal
Expiry Dates & Times	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)	12h00 on first Thursday of Feb, May, Aug & Nov (or previous business day if a public holiday)	12h00 on the first Thursday of the expiration month (or previous business day if a public holiday)	12h00 on the Monday preceding the third Wednesday of each month (or previous business day if a public holiday)	11h00 on third Wednesday of the contract month (or previous business day if a public holiday)
Quotations	Yield to maturity to 4 decimal places	Yield to maturity to 4 decimal places	Index Level (to three decimal places)	In Rand per Dollar to four decimals	100 minus the yield
Minimum Price Movement	One twentieth of a point (0.0005%)	One twentieth of a point (0.0005%)	0.001 Equal to R 10.00	0.0001 (R 10)	0.001 (R 2.50
Expiry Valuation Method	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry	Midpoint of best spot bid and offer yields advertised on Reuters at 12h00 expiry	As determined by the Bond Exchange of South Africa from primary dealer quotes at 12h00 on expiration day	Obtain notional offers to buy and sell U S $ 5,000,000 from six authorised dealers. Midpoint of each is calculated and the highest and lowest discarded. Average of the remaining four.	Based on the three month JIBAR rate as quoted on Reuters page SAFEY. The settlement price will be 100 minus JIBAR rounded to three decimal places
Settlement Method	Physically settled	Physically settled	Cash Settled in terms of rule 8.4.4	Cash settled	Cash settled
Clearing House Fees	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50	Futures R 1.00 Options R 0.50

(SAFEX, 2005)