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ABSTRACT:

This study provides an assessment of the comparative effectiveness of four methods of estimating the optimal hedge ratio in the South African equity and futures markets. This study bases the effectiveness of hedging on volatility reduction and minimisation of the coefficient of variation of hedged returns as well as the risk-aversion based on utility maximisation. The empirical analysis shows that the static single equation method estimated by ordinary least squares is the most effective over daily hedging periods. However, the vector error-correction method and multivariate GARCH methods are most effective over weekly and monthly hedging periods. Vector autoregression method is the least effective method over all hedging periods.
CONTENTS

Chapter One: Introduction ........................................................................................................... 5
  1.1. Background ............................................................................................................................ 5
  1.2. Research Question ............................................................................................................... 8

Chapter Two: Literature Review .............................................................................................. 11

Chapter Three: Methodology of Estimating the Optimal Hedge Ratio ............................... 19
  3.1. Discussion of Methodology ................................................................................................... 19
  3.2. Single Equation Method ...................................................................................................... 20
  3.3. Bivariate Vector Autoregression (VAR) Method .................................................................. 23
  3.4. Vector Error-Correction Method (VECM) ......................................................................... 24
  3.5. Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Method 25

Chapter Four: Data Analysis ...................................................................................................... 27
  4.1. Data Description .................................................................................................................... 27
  4.2. Test for Stationarity ............................................................................................................. 30
  4.3. Tests for Cointegration ....................................................................................................... 32

Chapter Five: Estimation of the Optimal Hedge Ratio ............................................................. 35
  5.1. Estimating the Optimal Hedge Ratio Using the Single Equation Method ............................ 35
  5.2. Estimating the Optimal Hedge Ratio Using the Bivariate Vector Autoregression (VAR) Method .................................................................................................................................. 36
  5.3. Vector Error-Correction (VECM) Method ......................................................................... 38
  5.4. Estimating the Optimal Hedge Ratio Using the Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Method .......................................................... 41
  5.5. Summary of Estimates of the Optimal Hedge Ratio ........................................................... 42

Chapter Six: Effectiveness of Hedging Methods ...................................................................... 43
  6.1. Discussion of Methodology ................................................................................................... 43
  6.2. Standard Deviation Analysis for Hedging Effectiveness ..................................................... 46
  6.3. Coefficient of Variation Analysis for Hedging Effectiveness ............................................. 47
  6.4. Risk-Aversion Based Utility Maximisation Analysis for Hedging Effectiveness. ............... 49

Chapter Seven: Conclusion ......................................................................................................... 53

List of References .......................................................................................................................... 55
CHAPTER ONE: INTRODUCTION

1.1. BACKGROUND

Global equity investors have consistently sought higher real returns. Developed markets such as the United States, Western Europe and Japan have provided investors with such returns throughout the 20th century, with few trading periods characterised by persistently poor returns. However, in the 21st century change appears, as developed markets have been plagued with persistent challenges such as the sub-prime crisis, the European debt-crisis, and the other elements of the global financial crisis. O’Neill (2001) popularly raised the profile of emerging markets as investment destinations in his treatise “The World Needs Better Economic BRICs”. This study highlighted current and potential economic advancements in four emerging markets: Brazil, Russia, India and China (BRIC). The study indicated that the economic potential of the BRIC nations would make them among the four most dominant economies by 2050.

Following O’Neill’s 2001 study, there have been several studies focused on emerging market financial market investment (Kabundi and Loots (2009); Edisona and Warnock (2008); Chari, Ouimet, and Tesar (2009); Kim and Wu (2008); Agmon and Messica (2009); Lien and Zhang (2008)). These studies encouraged investment in emerging financial markets by highlighting the prominent investment opportunities, as well as means to overcome the challenges. Grammatikos and Vermeulen (2011) detailed how the European debt crisis of the late 2000s and early 2010s as well as the fallout of the late 2000’s financial crisis further emphasised the importance of investing beyond developed world equity markets, as the challenges in the developed world eroded equity market returns across Europe and North America. Grammatikos and Vermeulen’s (2011) study also indicated that there was a transmission effect between increases in sovereign debt Credit Default Swap (CDS) spreads and the depreciation of Euro-zone stock indices. CDS spreads are used as a measure of the level of credit risk of a debt issuer relative to a benchmark debt issuer. In this case, the CDS spreads of European sovereign debt issuers were compared to benchmark U.S. treasury bills. European sovereign CDS spreads grew when the
perceived level of risk in European sovereign issuers rose, indicating a higher level of risk relative to U.S. sovereign debt issues. As the level of risk posed by European sovereign debt issues rose, this resulted in European stock markets experiencing strong negative shocks. Consequently, investors were poised to dedicate increasing portions of their funds to emerging markets, as the benefits of emerging market returns became more lucrative and uncertainty persisted in developed markets.

An economic report published by Goldman Sachs (Moe, Maasry, & Tang, 2010) indicated that emerging market equities are experiencing increasing shares in global equity portfolios. The report also indicated that they would continue to experience an increase in their share of global equity portfolios. Moe et al. (2010) expected emerging markets to contribute up to 55% of global equity market capitalisation by 2030. This finding, among other important indicators, shows an inclination of global investors to invest increasingly in emerging market equities instead of developed market equities due to higher expected real returns in emerging markets.

With high real returns available in emerging markets, investors have queried the risks associated with realising these returns. Thus, emerging market risk has increasingly become a field of interest to investors seeking to place capital in emerging markets, as studies by Angelidis (2010), Hearn et al. (2010) and Bekaert and Harvey (2002) have indicated. Hearn et al. (2010) highlighted the high risk premiums faced by emerging market equity investors relative to developed market equity investors. Thus, the mechanism and procedure for hedging equity market risk should be a priority for emerging market equity investors. Hedging equity market risk in emerging markets should reduce risk premiums and the level of risk faced by investors in emerging equity markets. In South Africa, the high liquidity of the Johannesburg Stock Exchange, compared to other African markets, increases the number of investors in the market (Hearn, Piesse, & Strange, 2010) and thus the number of investors that require effective hedging.
Hedging of equity exposure as an econometric risk management tool can be approached in various ways. Studies by Ederington (1979), Franckle (1980), Figlewski (1985), Vishwanath (1993), Ghosh (1993) and Chou et al. (1996), Myers (1991), Park and Switzer (1995), Holmes (1996), Laws and Thompson (2005) as well as Yang and Allen (2005) have applied up to six econometric hedging methods to estimate the optimal hedge ratio, a key metric in futures hedging. Thus, there are many econometric methods that can be used to estimate the optimal hedge ratio, such as the Single Equation Method estimated by Ordinary Least Squares (Ederington (1979), Franckle (1980) and Figlewski (1985)); the Vector Autoregression Method (Vishwanath (1993), Ghosh (1993) and Chou et al. (1996)); Vector Error-Correction Method (Vishwanath (1993), Ghosh (1993) and Chou et al. (1996)); and Multivariate GARCH methods (Myers (1991), Park and Switzer (1995) Wahab (1995)). Consequently, it is important to find the most effective hedging method.

However, due to the empirical nature of hedging, the most effective method of hedging equity market risk is dependent on multiple factors. According to Ederington (1979), Laws and Thompson (2005) as well as Yang and Allen (2005), the factors affecting the effectiveness of specific hedging methods in a particular market include: the equity market’s dynamics, the market’s relationship to other global equity markets, the hedging period required, and the derivative market depth. Empirical studies on hedging effectiveness need to be updated as the above factors change. When one updates a study on the optimal hedge ratio with more current data, the most effective method identified in the previous empirical study may change as the underlying factors change. As there are many hedging methods and the number of investors looking to place capital in South African markets is increasing (Hearn, Piesse, & Strange, 2010); the value of identifying the most effective hedging methods with recent data increases.

This empirical study identifies the most effective econometric hedging methods for the South African equity market during the period between 2008 and 2010. Thus, this study compares the effectiveness of econometric equity hedging methods during the global financial crisis period of 2008-2010.
1.2. **Research Question**

South Africa has been gaining prominence as an emerging market over the last few years, culminating in its inclusion in the most significant emerging market bloc, BRIC (Brazil, Russia, India and China) to form BRICS. Despite South Africa’s membership in the BRICS economic bloc, global investors and academics have not extensively researched the risks in South Africa’s well-developed equity market. The execution of an econometric risk analysis with an assessment of risk minimisation mechanisms for equity hedging in South Africa’s equity market during the crisis period is pending. Such an analysis could facilitate the influx of global capital into South African equity markets. Moreover, the shortage of research on stock index futures hedging in the South African equity markets is particularly patent, Degiannakis and Floros (2010) being among the few that have written on this topic.

This study addresses the void of knowledge on the most effective methods of estimating the optimal hedge ratio for the South African blue chip stock index, the FTSE/JSE Top 40, using stock index futures from the South African Futures Exchange (SAFEX) during the crisis period of 2008-2010. This study performs an empirical investigation; comparing the hedging effectiveness of four methods: a Single Equation Method estimated via Ordinary Least Squares (SEOLS); bivariate Vector Auto Regression (VAR) method; Vector Error Correction method (VECM); and Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH). Analyses the effectiveness of these methods will include assessments based on portfolio variance (volatility) reduction, minimisation of coefficients of variation and utility maximisation.

This study addresses the question: What is the most effective econometric method to hedge blue-chip equity exposure using index futures in South Africa during the 2008-2010 financial crisis period?
Given the significant interest in South Africa not only as a strong economic entity and investment destination but also as a gateway to other African markets, it is important to assess the effectiveness of hedging exposure in this market that houses many firms invested across the second fastest growing continental market in the world. There is significance in the assessment of the hedging of systematic risks inherent in the JSE Top 40 during the crisis period of 2008-2010. The significance comes from the need to ensure the consistent application of effective risk management in order to minimize losses and preserve capital. Currently, limited research has compared the effectiveness of equity futures hedging methods in the South African market. The study by Degiannakis and Floros (2010) did not thoroughly compare the hedging effectiveness of the methods used in the study. To address this limitation, this study identifies and encourages the application of the best methodology by assessing hedging effectiveness using three different approaches. This study utilises four frequently applied methods from literature on equity futures hedging. The empirical nature of this study would require updates of the results when market factors highlighted in the preceding section change.

The study will commence in chapter two, with a literature review. Chapter three is a review the methodology applied to estimate the optimal hedge ratio. Chapter four is an analysis of the data, highlighting the properties of the data set. Chapter five is the estimation of the point and time varying estimates of the optimal hedge ratio. Chapter six contains a review of the methodology for assessing the effectiveness of hedging strategies and an assessment of the effectiveness of hedging in terms of the volatility (standard deviation) reduction, size of the coefficient of variation and risk aversion based utility maximisation. Chapter seven is a summary of empirical results with an indication of possible opportunities for further research.
CHAPTER TWO: LITERATURE REVIEW

In hedging literature, there are several empirical studies on the estimation of the optimal hedge ratio. The ideas that lead to the development of the optimal hedge ratio started with Stein (1961) and Johnson (1960). Johnson (1960) intimated that hedging spot exposure with futures contracts could maximise the utility of portfolio holders by minimising the unconditional variance of portfolio returns. This is an important development, as it showed how to apply futures contracts effectively for hedging underlying exposure. Stein (1961) analysed the relationship between spot and futures prices and considered that some portion of exposure should be hedged and some should remain unhedged. Stein (1961) discussed a ratio of one-to-one of futures exposure to spot exposure on the hedged portion of portfolios; in subsequent literature, this ratio is the “naïve hedge ratio” or part of a “naïve hedging strategy”. It is “naïve” as one could hold futures contracts covering less exposure than the spot exposure held whilst still reducing the variance of portfolio returns and maximising utility. However, the optimal amount of futures exposure required per unit of spot of exposure was often hard to determine.

In a pioneering study, Ederington (1979) sought to find the optimal hedge ratio that would maximise utility. Ederington (1979) applied a constant hedge ratio from the Single Equation Method, with parameters estimated by the method of Ordinary Least Squares (SEMOLS), to estimate the optimal hedge ratio using time series regression with historical data on spot and futures prices. United States Treasury Bills (T-Bills) with various maturities where the underlying fixed-income instruments in this pioneering study, with T-Bill futures as hedging instruments. The estimated ratios were part of a hedging strategy applied to out-of-sample data to test their effectiveness. His study concluded that the SEMOLS outperforms the naïve (one-to-one) methodology by providing lower portfolio variance. Ederington’s (1979) study is important as it introduced a simple yet theoretically sound method of determining the optimal hedge ratio, frequently referred to as the minimum variance hedge ratio. Ederington’s (1979) methodology is widely applied in empirical studies including studies by Franckle
Franckle (1980) expanded on the work done by Ederington (1979) on fixed-income securities. Franckle (1980) agreed that matching a long T-Bill spot position with a short T-Bill futures position, proportional to the hedge ratio from the SEMOLS, improves hedging effectiveness compared to the naïve strategy. In addition, this study noted that adjusting the hedge ratio periodically, in response to changes in volatility, leads to a more effective hedge using T-Bill futures. Figlewski’s (1985) study assessed the effectiveness of stock index futures hedging, when they were first introduced, on the Kansas City Board of Trade in 1982. This study analysed various stock portfolios over multiple investment horizons with hedges using stock index futures. Figlewski (1985) identified the important phenomenon of basis risk in stock portfolios hedged by futures and highlighted how the risk needed to be managed by reducing hedges to periods. This study is significant as it indicated that static hedges are not effective over long hedging periods. After the studies of Franckle (1980) and Figlewski (1985), almost all studies on the optimal hedge ratio applied Ederington's (1979) SEMOLS including: Vishwanath (1993); Ghosh (1993) and Chou et al. (1996); Myers (1991); Park and Switzer (1995); Wahab (1995); Holmes (1996); Choudhry (2003); Laws and Thompson (2005); Yang and Allen (2005); as well as Bhaduria and Duraia (2008).

Figlewski’s (1985) study prompted an important question in financial economics literature: can one’s portfolio remain hedged ad infinitum with the same hedge ratio? Myers and Thompson (1989) in expanding on Figlewski’s (1985) assertions on basis risk, indicated that basis risk exists as changes in spot prices and changes in futures prices are not perfectly correlated. This inferred that optimal hedge ratios would have to be frequently recalculated whenever futures contracts expire and sometimes before expiry. Myers and Thompson's (1989) study was based on soft commodities futures hedging in Michigan, USA. Their study applied the bivariate VAR as well as the SEMOLS. Myers and Thompson (1989) further indicated that futures prices do not necessarily predict future spot prices and the hedge ratio is thus informationally inefficient, refuting earlier assertions of Stein (1961).
Another challenge faced in the estimation of the optimal hedge ratio using SEMOLS is the issue of cointegration. As most financial time series are non-stationary, their volatility changes over time. However, if changes in two financial time series, such as spot and futures prices based on the same underlying financial instrument have related changes in volatility, they are cointegrated and thus have a related or common trend. When cointegration exists, a Vector Error-Correction Method such as those expounded upon by Vishwanath (1993), Ghosh (1993), and Chou et al. (1996) has been applied to address the two limitations of hedge ratios from the SEMOLS, cointegration and serial correlation. Vishwanath (1993) estimated hedge ratios for soft commodities such as wheat, corn and soybeans hedged with soft commodity futures traded on the Chicago Board of Trade. Vishwanath (1993) expanded on the work done by Myers and Thompson (1989) by applying the VECM in addition to the VAR and SEMOLS. Ghosh’s (1993) study that covered equity futures hedging on the S&P 500 also indicated the strength of the vector-error correction method for effective hedging. Chou et al. (1996) applied the Vector Error-Correction Method, as well as methods such as the Single Equation Method and vector autoregression, when estimating hedge ratios for equity futures hedging with the Nikkei Stock Average Index.

The above studies indicated that the theoretically superior method of vector error-correction further improved utility. However, the challenge of frequent re-estimation of hedge ratios was still a challenge faced by users of this improved methodology.

In the late 1980’s, conditional time-varying volatility (heteroskedasticity), often observed in financial time series, became topical in literature after the groundbreaking studies by the Nobel economics laureate Robert Engle (1982) and Bollerslev, Engle and Wooldridge (1988) who extolled the value of Autoregressive Conditional Heteroskedasticity (ARCH) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) methods in dealing with conditional heteroskedasticity.
Univariate GARCH methodology would consider changes in volatility in spot or futures returns series independently, assuming a constant covariance. Multivariate GARCH methodology would consider changes in volatility in both spot and futures returns and the changes in their covariance. Wahab (1995) purported that Multivariate GARCH methodology provides unbiased parameter estimates compared to the univariate GARCH models for each variable. Wahab’s (1995) use of a Multivariate GARCH method to estimate hedge ratios for precious metals, such as gold and silver, was well specified, as it took into account the related time dependent variation of the two time series used for index futures hedging, the spot time series and the corresponding futures time series.

Multivariate GARCH methodology led to the estimation of time-varying optimal hedge ratios that provided the user with greater facility in the application of dynamic hedging. Studies that applied this methodology such as those by Myers (1991), Park and Switzer (1995) noted the superiority of hedge ratios from GARCH methods over the constant hedge ratios from methods such as the SEMOLS, VAR and VECM. Myers (1991) estimated time-varying hedge ratios and compared these estimates to constant estimates of the optimal hedge ratio, in terms of volatility reduction. Myers’ (1991) estimates were based on wheat futures traded on the Chicago Board of Trade. Park and Switzer (1995) estimated time varying hedge ratios with ARCH and GARCH models and compared them to constant hedge ratios from the SEMOLS and VAR. Park and Switzer (1995) also compared the estimated hedge ratios derived from the most traded equity index futures in North America: the major market index futures, Toronto 35 index futures, and the S&P 500 index futures. They also compared the three methods using portfolio variance (volatility) reduction. The studies indicated that GARCH methods reduced hedged portfolio variance more than other constant hedge ratio methods such as the SEMOLS and VAR.

Not all scholars however, hold this view; Lien (2005) contested the theoretical basis for the VECM superiority over the SEMOLS. Lien and Shrestha (2008) controversially asserted that the simple SEMOLS method is more effective than VECM and Multivariate GARCH methods. Lien and Shrestha (2008) further asserted that the computational complexity of GARCH methods were not
commensurate with the often marginal gains in variance reduction. The empirical nature of these studies leaves much room for divergent results depending on the subject market and the nature of the underlying financial instrument. Lien (2005) and Lien and Shrestha (2008) contributed to the growing body of literature analysing the comparative hedging effectiveness of various methods. This is increasingly important, as there are a variety of methods of estimating optimal hedge ratios.

Multiple studies have considered the effectiveness of hedging methods, such as those by Holmes (1996), Laws and Thompson (2005), and Yang and Allen (2005). Holmes (1996) chronicled the dynamics of stock index futures hedging in the United Kingdom. This was the first study where the effectiveness of FTSE 100 index futures was assessed since these futures were introduced in 1984. Holmes (1996) applied three econometric methods: the SEMOLS, VECM and GARCH. Holmes (1996) compared the effectiveness of these methods by assessing the reduction in the portfolio variance by applying each method over various hedging periods. This study concluded that the SEMOLS outperformed the more complex methods by reducing portfolio variance more than the other methods. Laws and Thompson (2005) compared the hedging effectiveness of stock index futures from the London International Financial Futures and Options Exchange on portfolios of stocks listed on the London Stock Exchange. In their study, the effectiveness of hedging is based on the reduction in portfolio variance. Laws and Thompson (2005) estimated the optimal hedge ratio with the SEMOLS and methods taking into account ARCH effects and effects Exponential Weighted Moving Average (EWMA). This study concluded that the method that takes into account EWMA effects was the most effective in reducing the portfolio variance. Yang and Allen (2005) performed an analysis of Multivariate GARCH methods for estimating hedge ratios in the Australian futures market. The underlying stock index therein was the All Ordinaries Index with its corresponding futures contract. Yang and Allen (2005) compared the time varying Multivariate GARCH methods to constant estimation methods using comparative reductions in portfolio variance and risk aversion based utility maximisation. This study concluded that the Multivariate GARCH method was the most effective hedging
The studies on the optimal hedge ratio detailed above, primarily apply evidence from developed markets. The body of knowledge therein is quite extensive, as developed markets have been the focus of most twentieth century financial research. Research focusing on emerging markets is considerably less abundant. Lien and Zhang (2008) surveyed 28 emerging markets and investigated the plausibility of effective hedging of financial market exposure in emerging markets. Lien and Zhang (2008) analysed several types of derivatives in multiple emerging markets in order to assess the effectiveness of hedging in volatile markets. This study showed that if structured strategies are affected, significant risk reduction is possible in various emerging markets. Olgun et al. (2012) produced a study covering the Turkish markets, where they estimated constant and time-varying hedge ratios for stock index futures on the Istanbul Stock Exchange’s ISE-30 index. Choudhry (2003) compared hedging effectiveness in three emerging markets to three developed markets. This study estimated hedge ratios with the traditional (naïve) method, SEMOLS, as well as time varying methods, such as the DVEC Multivariate GARCH and DVEC GARCH-X methods. Choudhry (2003) concluded that the DVEC GARCH method is the most effective method when assessed on out-of-sample data.

The above studies are among the small body of literature on stock index futures hedging in emerging markets. Studies that estimate optimal hedge ratios for stock index futures and analyse the effectiveness of methods are rare. One such study conducted by Bhaduria and Duraia (2008) applied data from India’s National Stock Exchange to assess the effectiveness of methods, such as the SEMOLS, VAR, VECM and the DVEC GARCH method. This study concluded that the GARCH model was moderately more effective than the SEMOLS over longer hedging periods and less effective over shorter periods.
Specifically for the South Africa, few studies cover the estimation of the optimal hedge ratio for equity investments. Degiannakis and Floros (2010) estimated hedge ratios for stock index futures in the South African market with data predating the financial crisis of the late 2000s. This is a rare study on optimal hedge ratios for stock index futures focusing on South Africa. However, a study is yet to perform an analysis of the relative effectiveness of the stock index futures hedging methods for the South African market. In addition, the data in the Degiannakis and Floros (2010) study predates the late 2000s crisis period and thus it is of interest to assess if the methods they highlighted are still are effective in the crisis period. This study estimates the optimal hedge ratio for the South African equity futures market utilising four frequently applied methods from economic literature on equity futures hedging: the SEMOLS, VAR, VECM and the DVEC GARCH method. In addition, this study includes an in-depth assessment of hedging effectiveness, lacking in the study by Degiannakis and Floros (2010).
CHAPTER THREE: METHODOLOGY OF ESTIMATING THE OPTIMAL HEDGE RATIO

3.1. DISCUSSION OF METHODOLOGY

This study applies multiple methods to estimate the optimal hedge ratio for the FTSE/JSE Top 40 index between 2008 and 2010. An assessment of the effectiveness of each method follows in the next chapter. This study generates point estimates using the Single Equation Method via Ordinary Least Squares regression (SEMOLS), Bivariate Vector Autoregression (VAR) and Bivariate Vector Autoregression with Vector Error-Correction Methodology (VECM). Following the point estimates, this study generates time varying estimates of the optimal hedge ratio by utilising a Multivariate Generalised Autoregressive Conditional Heteroskedasticity (MGARCH) approach.

Subsequent to the estimation of the hedge ratios, this study assesses hedging effectiveness through a number of methodologies such as volatility reduction, coefficient of variation minimisation and utility maximisation. It assesses the effectiveness of hedging against in-sample data as well as out-of-sample data over one, five and twenty day hedging periods. These different hedging periods represent daily, weekly and monthly investment horizons.
3.2. SINGLE EQUATION METHOD

This is the most commonly applied method of estimating the optimal hedge ratio first executed by Ederington (1979) in his pioneering study.

This simple yet conventional method of determining the optimal hedge ratio applies the following regression model, estimated by the method of Ordinary Least Squares:

\[ r_{st} = \alpha + \beta r_{ft} + \epsilon_t \]  \hspace{1cm} (1)

where \( \epsilon_t \) represents the error term from Ordinary Least Squares regression estimation. \( r_{st} \) and \( r_{ft} \) respectively represent continuously compounded returns on spot and futures indices. \( \beta \) represents the estimate for the optimal hedge ratio, \( h^* \).

The continuously compounded returns are calculated as follows:

\[ r_{st} = \ln(S_t) - \ln(S_{t-1}) \]
\[ r_{ft} = \ln(F_t) - \ln(F_{t-1}) \] \hspace{1cm} (2)

where \( S_t \) and \( F_t \) are spot and futures prices of the FTSE/JSE Top 40 index at time \( t \).

To simplify the expression, returns are expressed as follows:

\[ r_{st} = s_t - s_{t-1} \]
\[ r_{ft} = f_t - f_{t-1} \] \hspace{1cm} (3)

where \( s_t = \ln(S_t) \) and \( f_t = \ln(F_t) \).

The rationale behind using the \( \beta \) coefficient from the simple linear regression in equation (1) as an estimate for the optimal hedge ratio \( h^* \) is as follows:

The value a long spot portfolio hedged with a short futures position can be represented in equation (4).
\[ V_t = Q_S S_t - Q_F F_t, \quad (4) \]

where \( V_t \) is the value of the hedged portfolio, \( Q_S \) and \( Q_F \) are the respective quantities of long spot units and futures units held in the portfolio. \( S_t \) and \( F_t \) represent the respective prices of one unit of spot and futures exposure.

The hedge ratio, \( h \), is the ratio of the quantity of futures units held for each spot unit held. Equation (4) can be restated per unit of spot exposure in terms of \( h \), as depicted in equation (5).

\[ V_t = S_t - hF_t, \quad (5) \]

where \( h = \frac{Q_F}{Q_S} \) is the hedge ratio.

Given the structure of equation (5), portfolio returns can be expressed in terms of the hedge ratio, as depicted in equation (6).

\[ r_t = r_{st} - hr_{ft}, \quad (6) \]

The variance of portfolio returns is as expressed in equation (7).

\[ \sigma_p^2 = \sigma_{st}^2 - 2h\sigma_{sf} + h^2\sigma_f^2, \quad (7) \]

\[ \therefore \sigma_p^2 = \sigma_{st}^2 - 2h\sigma_{sf} + h^2\sigma_f^2 \]

The next step involves minimising the portfolio variance, \( \sigma_p^2 \), by choosing an optimal hedge ratio, \( h^* \). The minimisation problem is solved via differential calculus by setting \( \frac{\partial \sigma_p^2}{\partial h} \) to zero, and solving for \( h \). The optimal hedge ratio, \( h^* \), is the solution to this partial differential equation as depicted in equation (8).
\[ \frac{\partial \sigma^2}{\partial h} = -2\sigma_s + 2h\sigma_f \]

\[ \therefore \frac{\partial \sigma^2}{\partial h} = 0 \]

\[ \Rightarrow h^* = \frac{\sigma_s}{\sigma_f}, \quad (8) \]

The method of Ordinary Least Squares is used to estimate the parameters in equation (1). This method seeks to determine \( \alpha \) and \( \beta \) such in a manner that minimises the sum of the squared errors, \( Q = \sum_{vt} \varepsilon_t^2 \).

The minimisation problem is expressed in equation (9).

\[ \min_{\alpha, \beta} Q(\alpha, \beta) \]

\[ \min_{\alpha, \beta} \sum_{vt} \varepsilon_t^2 \]

\[ \min_{\alpha, \beta} \sum_{vt} (r_{st} - \alpha + \beta r_{ft})^2, \quad (9) \]

The variables in equation (9) are defined in equation (1).

The estimated solutions to equation (9) via differential calculus are depicted in equation (10):

\[ \beta = \frac{\sigma_s}{\sigma_f} \]

\[ \alpha = E[r_{st}] - \beta E[r_{ft}], \quad (10) \]

As equations (8) and (10) indicate, \( \beta = h^* \) therefore, \( \beta \) in equation (1) represents an estimate for the optimal hedge ratio.
3.3. **Bivariate Vector Autoregression (VAR) Method**

A major shortcoming of the Single Equation Method using OLS, as argued by Herbst et al. (1989), is that it does not address the problem of serial correlation among the residuals of the endogenous variables, which, in this case, are the returns series. The bivariate VAR addresses the problem faced by serial correlation by modelling the different endogenous variables utilising the bivariate VAR structure as follows:

\[
\Delta s_t = \alpha_s + \sum_{i=1}^{m} \beta_{si} \Delta s_{t-i} + \sum_{i=1}^{m} \gamma_{si} \Delta f_{t-i} + \lambda s Z_{t-1} + \epsilon_{st}
\]

\[
\Delta f_t = \alpha_f + \sum_{i=1}^{m} \beta_{fi} \Delta s_{t-i} + \sum_{i=1}^{m} \gamma_{fi} \Delta f_{t-i} + \lambda f Z_{t-1} + \epsilon_{ft},
\]

where \(\Delta s_t = \ln(S_t) - \ln(S_{t-1})\) and \(\Delta f_t = \ln(F_t) - \ln(F_{t-1})\). \(\alpha_s\) and \(\alpha_f\) are the intercepts, \(\beta_{si}\), \(\beta_{fi}\), \(\gamma_{si}\) and \(\gamma_{fi}\) are parameters and \(\epsilon_{st}\) and \(\epsilon_{ft}\) are independently identically distributed random vectors.

The optimal lag length, \(m\), is determined by repeating the model using different lags and selecting the optimal lag length based on Schwarz Bayesian Criterion developed by Schwarz (1978). Once the optimal lag length is determined, residual time series of \(\Delta s_t\) and \(\Delta f_t\) are estimated and used to estimate the optimal hedge ratio.

The estimate of the optimal hedge ratio in this case is defined as the ratio that yields the minimum variance, or the minimum variance hedge ratio, \(h^*\), defined as follows:

\[
h^* = \frac{\sigma_{sf}}{\sigma_f^2},
\]

where \(\sigma_{sf}\) is the covariance between the residuals of \(\Delta s_t\) and the residuals of \(\Delta f_t\) and \(\sigma_f^2\) is the variance of the residuals of \(\Delta f_t\). This is in line with the derivation applied earlier that resulted in equation (8).
3.4. Vector Error-Correction Method (VECM)

Vishwanath (1993), Ghosh (1993) and Chou et al. (1996) discussed a shortcoming of the SEMOLS and VAR, cointegration. This occurs when the levels of two time series, such as spot and futures prices, are non-stationary and are integrated of order one. When this occurs, their variances vary with time, however, this variation is related, and this related time dependent variation is called cointegration.

The Vector Error-Correction Method addresses this by adding an error-correction to the error terms of each variable in the vector autoregression to account for the long-term equilibrium relationship of spot and futures price movements. The execution of the Vector Error-Correction Method is as follows:

\[
\Delta s_t = \alpha_s + \sum_{i=1}^{m} \beta_{si} \Delta s_{t-i} + \sum_{i=1}^{m} \gamma_{si} \Delta f_{t-i} + \lambda_s Z_{t-1} + \varepsilon_{st}
\]

\[
\Delta f_t = \alpha_f + \sum_{i=1}^{m} \beta_{fi} \Delta s_{t-i} + \sum_{i=1}^{m} \gamma_{fi} \Delta f_{t-i} + \lambda_f Z_{t-1} + \varepsilon_{ft},
\]

where \(\Delta s_t = \ln(S_t) - \ln(S_{t-1})\) and \(\Delta f_t = \ln(F_t) - \ln(F_{t-1})\). \(Z_{t-1} = s_{t-1} - C - \delta f_{t-1}\) is the error correction term with \(\delta\) as the cointegrating factor, \(C\), as a constant and \(\lambda_s, \lambda_f\) as adjustment parameters.

Following the estimation of parameters in the VECM, the hedge ratio is estimated using a similar procedure to the standard Vector Autoregression Method (see section 3.3). The residual series are generated and their variances and covariances are utilized to estimate the optimal hedge ratio as depicted in equation (12).
3.5. **Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Method**

The major shortcoming shared by the SEMOLS, the VAR, and the VECM is the risk of Autoregressive Conditional Heteroskedasticity (ARCH) effects in the residuals, which occurs when the variance of a time-series changes significantly with the passage of time. This property is common among financial time series as indicated by Bollerslev, Engle and Wooldridge (1988).

Heteroskedasticity, as indicated by Myers (1991) as well as Park and Switzer (1995), invalidates hedge ratio estimates made by the first three methods used in this study, due to model misspecification. Myers (1991), Park and Switzer (1995), as well as Wahab (1995) purported that the application of Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) methods provide more effective and unbiased estimates of the optimal hedge ratio.

Bollerslev, Engle and Wooldridge (1988) proposed the Multivariate GARCH method, which deals with ARCH effects in multiple time series by generating time-varying second order moments to allow for time series of variances.

The Multivariate GARCH method is a generalised version of the univariate GARCH method that takes into account the related time-varying variation in the analysed time series. A conventional MGARCH with ARCH components of order one and GARCH components of order one, MGARCH(1,1) is formulated as follows:

\[
\begin{bmatrix}
    h_{ss} \\
    h_{sf} \\
    h_{ff}
\end{bmatrix}_t =
\begin{bmatrix}
    Y_{ss} \\
    Y_{sf} \\
    Y_{ff}
\end{bmatrix}_t +
\begin{bmatrix}
    \alpha_{11} & \alpha_{12} & \alpha_{13} \\
    \alpha_{21} & \alpha_{22} & \alpha_{23} \\
    \alpha_{31} & \alpha_{32} & \alpha_{33}
\end{bmatrix}
\begin{bmatrix}
    \varepsilon_s^2 \\
    \varepsilon_f^2
\end{bmatrix}_t +
\begin{bmatrix}
    \beta_{11} & \beta_{12} & \beta_{13} \\
    \beta_{21} & \beta_{22} & \beta_{23} \\
    \beta_{31} & \beta_{32} & \beta_{33}
\end{bmatrix}
\begin{bmatrix}
    h_{ss} \\
    h_{sf} \\
    h_{ff}
\end{bmatrix}_{t-1},
\]

where $h_{ss}$, $h_{ff}$ and $h_{sf}$ are the respective conditional variances of the spot and futures returns’ residuals and their conditional covariance with a constant mean model as the mean equation.
Equation (7) can be represented in matrix form as follows:

\[ H_t = \Gamma_t + A \times E + B \times H_{t-1}, \quad (15) \]

Due to the large number of parameters that are required to apply the estimate the model for \( H_t \), Bollerslev, Engle and Wooldridge (1988) suggested a parameterisation of the conditional variance equation in the GARCH model, \( H_t \), the DVEC MGARCH model that allows for a less computationally intensive method of estimating the variances and covariances. The DVEC model sets the off-diagonal elements of \( A \) and \( B \) from equation (14) to zero, which reduces the number of parameters to be estimated and reduces the system of linear equations below:

\[
\begin{align*}
    h_{ss}^t &= \gamma_{ss} + \alpha_{11} \varepsilon_{s,t-1}^2 + \beta_{11} h_{ss,t-1} \\
    h_{sf}^t &= \gamma_{sf} + \alpha_{22} \varepsilon_{s} \varepsilon_{f} + \beta_{22} h_{sf,t-1} \\
    h_{ff}^t &= \gamma_{ff} + \alpha_{33} \varepsilon_{f,t-1}^2 + \beta_{33} h_{ff,t-1}, \quad (16)
\end{align*}
\]

With the above estimated, the time varying hedge ratio is defined in a similar way to the way defined in the bivariate VAR model with a time varying subscript added, indicating time-varying variances and covariances.

\[ h_t^* = h_{sft} / h_{fft}, \quad (17) \]

This DVEC MGARCH model take into account time-varying conditional variances and correlation between spot and futures prices and thus produces time varying estimates of the optimal hedge ratio.
CHAPTER FOUR: DATA ANALYSIS

4.1. DATA DESCRIPTION

This study assesses the effectiveness of methodology for estimating the optimal hedge ratio during the financial crisis period of the late 2000s and its aftermath, where irregular market volatility was present. For this reason, the sample commences in 2008. The persistent equity market volatility resulting from the prolonged European debt crisis justifies the extension of the sample to 2010.

The data applied in this study is daily closing spot prices for the FTSE/JSE All Share Top 40 index (ALSI Top 40) traded on the Johannesburg Stock Exchange (JSE), as well as daily closing prices for the ALSI Top 40 future with the nearest maturity, traded on the South African Futures Exchange (SAFEX). The data period ranges from the 2nd of January 2008 to the 31st of December 2010 for in-sample data. Out-of-sample data covers sample data from the 3rd of January 2011 to 15th of June 2011.

The data applied is from the I-Net Bridge as well as BFA McGregor databases. Figure 1 presents the spot index returns for in-sample data. There appears to be a surge in volatility in 2008, which is likely a result of the various financial crisis events of 2008, such as the collapse of Lehman Brothers. A lesser surge in volatility occurs in 2010, which likely represents the market response to the European debt crisis.
The futures returns of in-sample data appear highly correlated to the spot returns, depicted in Figure 2.
Figures 2 and 3 indicate that the volatility of the spot and futures returns series change with time in a similar manner; this is a potential indication of stationarity and cointegration. This could affect the specification of the models applied to estimate the optimal hedge ratio. Thus, tests for stationarity and cointegration, prior to estimating models, would limit model misspecification.
4.2. **Test for Stationarity**

This section performs tests for stationarity in order to ensure correct model specification. Time varying probability distributions for returns may lead to biased estimates of the optimal hedge ratio with methods, such as the Single Equation Method and vector autoregression. The vector error correction and Multivariate GARCH methods should be applied when the presence of non-stationarity is detected.

Table 1 presents the results of unit root tests for the natural logarithms of spot and futures prices as well as their first differences, which are continuously compounded spot and futures returns.

**TABLE 1: TESTS FOR UNIT ROOTS**

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Test statistic</th>
<th>ADF p-value</th>
<th>KPSS test statics</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnS</td>
<td>-1.68550</td>
<td>0.75700</td>
<td>0.63188*</td>
</tr>
<tr>
<td>lnF</td>
<td>-1.68899</td>
<td>0.75550</td>
<td>0.62270*</td>
</tr>
<tr>
<td>Rs</td>
<td>-26.54140*</td>
<td>0.00000</td>
<td>0.23357</td>
</tr>
<tr>
<td>Rf</td>
<td>-26.35735*</td>
<td>0.00000</td>
<td>0.24450</td>
</tr>
</tbody>
</table>

The asterisk (*) represents the presence of stationarity at a 5% level of significance.

The statistics in the Table 1 include augmented Dickey-Fuller (ADF) test statistics as well as Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test statistics. The numbers in bold indicate the rejection of the null hypothesis at a 5% level of significance.

The ADF test, developed by Dickey and Fuller (1981), has a null hypothesis that the variables contain a unit root and are thus non-stationary. The results in Table 1 indicate that the natural logarithms of spot and futures prices are non-stationary according to the ADF test. The continuously compounded returns are however, stationary at a 5% level of significance.
The power of unit root tests with null hypotheses of non-stationarity was challenged by Schwert (1987), as well as DeJong and Whiteman (1991), whose studies indicated that these tests often experience Type II errors. Type II errors infer that these tests tend to accept the null hypothesis of non-stationarity when the alternative hypothesis of stationarity is true. The prevalence of Type II errors is attributed to low power of the test against stable autoregressive alternatives with roots close to unity. The ADF test has a null hypothesis of non-stationarity, for this reason, the study also performed different tests for stationarity, KPSS tests. The KPSS tests, developed by Kwiatkowski et al. (1992) have a null hypothesis of that a series is stationary around a deterministic level or a deterministic trend. One rejects the null hypothesis of stationarity if the KPSS statistics are large relative to asymptotic critical values.

Table 1 indicates that the natural logarithms of spot and futures prices are level and trend non-stationary at a 5% level of significance, according to the test statistics of the KPSS test, thus confirming the results of the ADF test. The continuously compounded returns are level stationary and trend stationary, as their KPSS test statistics are small, at a 5% level of significance.

The natural logarithms of the price series are thus non-stationary and their first differences, the continuously compounded returns series, are non-stationary. This lessens the bias of estimating the optimal hedge ratio using the Single Equation Method and the Vector Autoregression Methods.

The elimination of unit roots by differencing may indicate that the spot and futures price processes are integrated to order one.
4.3. **Tests for Cointegration**

Given that the spot and futures price series are integrated to order one, there may be a cointegrating relationship between them. A cointegrating relationship exists when variables are integrated of the same order greater than zero. If a cointegrating relationship exists, time series analysis of non-stationary variables can yield valid econometric results (Engle & Granger, 1987).

Table 2 presents the results from the tests for cointegration proposed by Johansen (1991):

**TABLE 2: JOHANSEN’S TEST FOR COINTEGRATION**

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>$H_1$</th>
<th>Maximum eigenvalue statistic</th>
<th>Trace statistic</th>
<th>Maximum-eigenvalue test p-value</th>
<th>Trace test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 0$</td>
<td>$r &lt; 1$</td>
<td>0.03056</td>
<td>23.2743*</td>
<td>25.18332*</td>
<td>0.0015</td>
</tr>
<tr>
<td>$r = 1$</td>
<td>$r &lt; 2$</td>
<td>0.00254</td>
<td>1.9091</td>
<td>1.90905</td>
<td>0.1671</td>
</tr>
</tbody>
</table>

The asterisk (*) represents statistical significance at a 5% level of significance.

The cointegration tests applied in this study are unrestricted cointegration rank tests (trace and maximum eigenvalue) that use likelihood ratios based on the maximum eigenvalue or the trace of the stochastic matrix. $r$ represents the number of linearly independent cointegrating vectors (relationships). The test based on the maximum eigenvalue statistic tests a null hypothesis of $r$ cointegrating relations against an alternative hypothesis of $(r + 1)$ cointegrating relations. The maximum eigenvalue statistic is computed as follows:

$$LR_{max}(r|r + 1) = -TLn(1 - \lambda_i), \quad (18)$$

where $LR$ is the likelihood ratio, $T$ is the number of observations, and $\lambda_i$ represents the $i^{th}$ smallest squared canonical correlation derived by Johansen (1991).
The test based on the trace statistic tests, a null hypothesis of \( r \) cointegrating relations against an alternative hypothesis of \( k \) cointegrating relations. The trace statistic is computed as follows:

\[
LR_{tr}(r|k) = -T \sum_{i=1}^{r+1} Ln(1 - \lambda_i), \quad (19)
\]

where LR is the likelihood ratio, \( T \) is the number of observations, \( k \) is the number of endogenous variables and \( \lambda_i \) represents the \( i^{th} \) smallest squared canonical correlation derived by Johansen (1991).

The null hypotheses of Johanesen's tests for cointegration are that there are at most a fixed number of cointegrating vectors (in this case zero or one). The alternative hypothesis is that the number of cointegrating vectors is less than the next largest integer (in this case one and two). As the p-values for both the trace and maximum eigenvalue tests in Table 2 indicate, the null hypothesis of no cointegrating vectors is rejected at a 1% level of significance and the null hypothesis of one cointegrating vector is not rejected at a 1% level of significance. One can conclude that the time series have a cointegrating relationship with a rank of one.

The presence of cointegrating relationships between the price series indicated a benefit in the application of Vector Error-Correction Methods to estimate the optimal hedge ratio.
CHAPTER FIVE: ESTIMATION OF THE OPTIMAL HEDGE RATIO

5.1. ESTIMATING THE OPTIMAL HEDGE RATIO USING THE SINGLE EQUATION METHOD

The first method applied to estimate the optimal hedge ratio is the Single Equation Method via Ordinary Least Squares (SEMOLS) regression of the continuously compounded spot and futures returns as earlier denoted in equation (1). The $\beta$ coefficient of the regression is the estimate of the optimal hedge ratio, as derived earlier.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.00002</td>
<td>0.014</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.98410*</td>
<td>0.00749</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.95838</td>
<td></td>
</tr>
</tbody>
</table>

The asterisk (*) represents statistical significance at a 5% level of significance.

Table 3 indicates that the hedge ratio in this context is 0.9584 futures contracts per unit of underlying spot diversified portfolio (FTSE/JSE Top40) held. It is important to note that the $\beta$ coefficient is statistically significant at a 5% level of significance, based on the coefficient’s p-value, which is less than 5%.

A challenge faced by the SEMOLS is that it does not account for serial correlation of the residuals. Table 4 indicates that the Q-statistics of the residuals from the Single Equation Method are statistically significant indicating the presence of serial correlation.

<table>
<thead>
<tr>
<th>Lags</th>
<th>Autocorrelation coefficient</th>
<th>Q-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.38900</td>
<td>114.19000*</td>
<td>0.00000</td>
</tr>
<tr>
<td>5</td>
<td>-0.04900</td>
<td>122.88000*</td>
<td>0.00000</td>
</tr>
<tr>
<td>20</td>
<td>0.02500</td>
<td>139.08000*</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

The asterisk (*) represents statistical significance at a 5% level of significance.
This challenge of serial correlation can be addressed by applying vector autoregression.

Another challenge faced by the SEMOLS is that it assumes that the spot return is a function of the futures return. This challenge of having to determine whether the futures or spot return is the endogenous variable can also be addressed by applying vector autoregression.

5.2. **ESTIMATING THE OPTIMAL HEDGE RATIO USING THE BIVARIATE VECTOR AUTOREGRESSION (VAR) METHOD**

The second method applied to estimate the optimal hedge ratio is the Bivariate Vector Autoregression Method. This method assumes all variables are endogenous. The continuously compounded returns of the spot and futures prices are the endogenous variables for this VAR model, as earlier depicted in equation (11). The optimal lag length, \( m \), is two, as determined by the Bayesian information criterion developed by Schwarz (1978). Table 5 contains the estimates for equation (11) for the optimal lag length of three.

<table>
<thead>
<tr>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \gamma_1 )</th>
<th>( \gamma_2 )</th>
<th>( \alpha )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_{st} )</td>
<td>( r_{ft} )</td>
<td>( r_{st} )</td>
<td>( r_{ft} )</td>
<td>( r_{st} )</td>
</tr>
<tr>
<td>-0.17624</td>
<td>0.25149</td>
<td>(0.19631)</td>
<td>(0.19515)</td>
<td>-0.14260</td>
</tr>
</tbody>
</table>

The values of the coefficients are in bold and the standard errors are parenthesis. The asterisk (*) represents statistical significance at a 5% level of significance.

The residuals of the VAR model, rather than the parameter estimates, are the important data points required to estimate the optimal hedge ratio. The time series of the residuals of \( \varepsilon_{st} \) and \( \varepsilon_{ft} \) from equation (11) are generated by taking
the difference of the returns estimated by the VAR model and the actual returns from the in-sample data set.

Upon generation of the time series of the residuals of the bivariate VAR model, equation (12) is applied to estimate the optimal hedge ratio. The inputs for equation (12) are the variance of the residuals of the futures returns and the covariance of the residuals of the spot and futures returns. Table 6 contains the estimate for the optimal hedge ratio using the bivariate VAR model, as well as the direct inputs to equation (12).

### Table 6: Hedge Ratio Estimates Using the Bivariate VAR

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma_{sf} )</td>
<td>0.00034</td>
</tr>
<tr>
<td>( \sigma_f^2 )</td>
<td>0.00034</td>
</tr>
<tr>
<td>( h^* )</td>
<td>0.98852</td>
</tr>
</tbody>
</table>

The tests in section 4.3 indicate the presence of a cointegrating relationship between spot and futures prices. This indicates that the Vector Error-Correction Method can improve the model specification and reduce the bias of the estimate of the optimal hedge ratio.
5.3. **Vector Error-Correction (VECM) Method**

The Vector Error-Correction Method is the next method applied to estimate the optimal hedge ratio. This method adds error-correction terms to VAR model in equation (11) to yield equation (13).

The estimates for the VECM are presented in Table 7.

<table>
<thead>
<tr>
<th>Table 7: Estimates Using the VECM Bivariate VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>$\lambda$</td>
</tr>
<tr>
<td>$\beta_1$</td>
</tr>
<tr>
<td>$\beta_2$</td>
</tr>
<tr>
<td>$\gamma_1$</td>
</tr>
<tr>
<td>$\gamma_2$</td>
</tr>
<tr>
<td>$\alpha$</td>
</tr>
</tbody>
</table>

The cointegrating equation:

- $S_{t-1} = 1.00000$
- $F_{t-1} = -1.01291^*$
- $C = -0.00002$

The values of the coefficients are in bold and the standard errors are parenthesis

The asterisk (*) represents statistical significance at a 5% level of significance

From the speed of the adjustment parameters, $\lambda_s$ and $\lambda_f$, only the adjustment parameter for the futures equation, $\lambda_f$, is significant, indicating that the futures index is converging to movements in the spot index and not vice versa. This indicates that the futures price series adjusts more rapidly to the previous period’s deviation from the long-run equilibrium than the spot price series.

Similar to the bivariate VAR, the VECM residuals are generated to estimate the optimal hedge ratio using equation (12). Table 8 presents the estimate for the optimal hedge ratio and the direct inputs.
Figure 3 and Figure 4 depict the spot and futures residuals of the VAR model. Prior to testing for conditional heteroskedasticity, Figure 3 and Figure 4 suggest the residuals of both series appear to exhibit time varying volatility or ARCH effects.

This study uses White’s (1980) method to test for the presence of conditional heteroskedasticity (ARCH effects). Table 9 presents the results for White’s test (with and without cross-terms). The null hypothesis for White’s test is homoskedasticity and the alternative is heteroskedasticity. As the p-values are zero at five decimal places, one can reject null hypothesis in favour of the alternative of heteroskedasticity.

<table>
<thead>
<tr>
<th>White test type</th>
<th>$\chi^2$ statistic</th>
<th>Degrees of freedom</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-terms</td>
<td>298.3345</td>
<td>42.0000</td>
<td>0.00000</td>
</tr>
<tr>
<td>No cross-terms</td>
<td>107.8269</td>
<td>24.0000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

The ARCH effects present in the data can be addressed by estimating the optimal hedge ratio using a Multivariate GARCH approach.
FIGURE 3: VAR SPOT RETURN RESIDUALS

FIGURE 4: VAR FUTURES RETURNS RESIDUALS
5.4. **Estimating the Optimal Hedge Ratio Using the Multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Method**

The Multivariate GARCH Method applied herein is a DVEC GARCH model that addressed ARCH effects by explicitly modelling the conditional variance and covariances of the residuals of the spot and future returns. Studies by Yang and Allen (2005), Bhaduria and Duraia (2008), and Olgun and Yetkiner (2012) have applied the DVEC GARCH model to estimate time-varying hedge ratios because the DVEC GARCH model allows for time-varying conditional covariances (Bollerslev, Engle, & Wooldridge, 1988). The time series of conditional variances and covariances are the series data required to estimate time-varying hedge ratios.

Table 10 presents the estimation results from equation (16) the DVEC Multivariate GARCH Model. The constant mean function is used as the mean equation for this GARCH model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{ss}$</td>
<td>0.00001</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\gamma_{sf}$</td>
<td>0.00001</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\gamma_{ff}$</td>
<td>0.00002</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\alpha_{11}$</td>
<td>0.19998</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\alpha_{22}$</td>
<td>0.20884</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\alpha_{33}$</td>
<td>0.22207</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.77910</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>0.76238</td>
<td>0.00000</td>
</tr>
<tr>
<td>$\beta_{33}$</td>
<td>0.74206</td>
<td>0.01654</td>
</tr>
</tbody>
</table>

* Statistically significant at a 5% level of significance

Dynamic hedge ratios are estimated by applying the variances and covariances of the residuals of the GARCH model to equation (17) to determine time-varying hedge ratios. These time-varying hedge ratios are presented in Figure 5.
5.5. SUMMARY OF ESTIMATES OF THE OPTIMAL HEDGE RATIO

The hedge ratio estimates from the different methods are summarised in Table 11. The VECM method produces the most conservative hedge ratio of 99.8% compared to the more aggressive hedge ratios of the OLS and VAR methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>( h^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single equation (OLS)</td>
<td>0.98410</td>
</tr>
<tr>
<td>Bivariate VAR</td>
<td>0.98852</td>
</tr>
<tr>
<td>VECM</td>
<td>0.99812</td>
</tr>
<tr>
<td>DVEC-MGARCH</td>
<td>Time-varying</td>
</tr>
</tbody>
</table>
CHAPTER SIX: EFFECTIVENESS OF HEDGING METHODS

6.1. DISCUSSION OF METHODOLOGY

Hedging effectiveness is important as it allows users of hedging methods to assess the quality of their hedges. Following the application of one of the econometric methods discussed earlier to estimate the optimal hedge ratio (whether static or dynamic), the hedge ratios estimated are used to create hedging strategies. The hedging strategy involves a portfolio comprised of a long position in the underlying equity index as well as a short position in futures contracts proportionate to the estimate of the optimal hedge ratio. A portfolio comprised as such is a hedged portfolio; a portfolio comprising of an equivalent long spot exposure to the hedged portfolio is an un-hedged portfolio.

In order to perceive effectiveness, a comparison of some kind must be made. This comparison is between the hedged and un-hedged portfolio. In order to compare these two portfolios the key benefits that the hedged portfolio provides must be quantified.

The first way the benefits of hedging can be quantified is in terms of the reduction in volatility as intimated by Johnson (1960) and Ederington (1979). In this study, volatility is expressed by the standard deviation of the returns. Volatility presents the investor with uncertainty regarding the portfolio’s value and therefore, the lower the volatility (standard deviation) of the hedged portfolio, relative to the un-hedged portfolio, the more effective the hedge.

The returns of the hedged and un-hedged portfolios are defined as follows:

\[ r_{Ut} = r_{st} \]
\[ r_{Ht} = r_{st} - h^* \times r_{ft}, \]  \hspace{1cm} (21)

where \( r_{Ut} \) is the return on the un-hedged portfolio that only comprises of the underlying stock index, \( r_{Ht} \) is the return on the hedged portfolio as derived earlier in equation (6), \( h^* \) is the optimal hedge ratio, and \( r_{st} \) and \( r_{ft} \) are defined as per equation (2).
Based on return estimated in equation (21) one can determine the equations for the variances of the un-hedged and hedged portfolios as follows:

\[ \sigma_U^2 = \sigma_s^2 \]

\[ \sigma_H^2 = \sigma_s^2 - 2h^* \times \sigma_{sf} + h^{*2} \times \sigma_f^2, \quad (22) \]

where \( \sigma_U^2 \) and \( \sigma_H^2 \) are the variance of the un-hedged and hedged portfolios; \( \sigma_s^2 \), \( \sigma_f^2 \) and \( \sigma_{sf} \) are variances and covariance of the spot and futures returns respectively.

Based on the definitions of the variances of the hedged and un-hedged portfolio, in equation (22), one can compare the standard deviations (volatilities) of the hedged portfolio against the un-hedged portfolio. The volatility reduction of the hedged portfolio relative to the un-hedged portfolio is a measure of hedging effectiveness, as this indicates how much uncertainty has been removed from the portfolio by hedging. The volatility reduction percentage is determined by taking the difference in volatility of the two portfolios' and dividing the difference by the volatility of the un-hedged portfolio, as depicted in equation (23):

\[ \frac{\sigma_U - \sigma_H}{\sigma_U}, \quad (23) \]

In accordance with Ederington's (1979) work, a higher ratio in equation (23) infers a more effective hedge, because the reduction in hedged portfolio's volatility is higher relative to the un-hedged portfolio.

Another method of comparing the effectiveness of hedging is comparing the coefficient of variation of the hedged portfolio against that of another hedged portfolio (Jianru & Jinghua, 2011). The coefficient of variation is the ratio of the standard deviation over the expected return. In this context, it represents the amount of risk that needs to be taken per unit of return. Thus, a portfolio with a small coefficient of variation is less risky than a portfolio with a larger coefficient of variation, relative to their respective levels of returns.

The coefficient of variation for a hedged portfolio is defined in equation (24):

\[ \frac{\sigma_H}{r_H}, \quad (24) \]
Although a coefficient of variation comparison takes into account the relative level of return for when comparing volatility reduction, it does not take investors’ level of risk aversion into account. This study uses a utility-based comparison as applied by Gagnon et al. (1998) as well as Yang and Allen (2005), to take an investors’ degree of risk aversion into account in the comparison of hedging effectiveness.

Gagnon et al. (1998) represented the utility problem as follows:

$$\max_h \left[ E(r_{ht}|\Omega_{t-1}) - \frac{1}{2} \phi Var(r_{ht}|\Omega_{t-1}) \right],$$  \hspace{1cm} (25)

where \( r_{ht} \) is defined in equation (21), \( \phi \) is the level of risk aversion and \( \Omega_{t-1} \) is the historical data available at time \( t - 1 \).

For an investor that is a mean-variance optimiser, if \( \phi \) is large (\( \phi > 1 \)) there is a high level of risk aversion and if \( \phi \) is low (\( 0 < \phi < 1 \)) there is a low level of risk aversion. If \( \phi \) is zero, the investor is risk neutral thus for a given level of return, the investor neither loses utility by taking on higher levels of risk nor does the investor gain utility by reducing levels of risk. Risk in this context is represented by the variance of returns on the hedge portfolio, \( Var(r_{ht}|\Omega_{t-1}) \). As \( \phi \) increases positively from zero, a risk-averse investor experiences a higher penalty on utility by taking on higher levels of risk to gain a particular return. A risk-seeking investor would have a \( \phi \) less than zero. Such an investor would gain utility by experiencing higher levels of risk to obtain a given return.

The utility maximisation method generally allows some flexibility in terms of how it addresses the investors’ degree of risk aversion by allowing investors’ to choose an optimal hedge ratio that will maximise utility at varying levels of risk aversion. In this study, the focus is on applying the utility-maximisation method to compare the level of investors’ utility when there is no hedging and when hedging is executed with the estimates of the optimal hedge ratio developed earlier in the study. At specified degrees of risk aversion, the hedge ratios from different estimation methods are compared to assess the degree of utility improvement experienced by holding the hedged portfolio compared to holding the un-hedged portfolio.
The above methods of comparing the effectiveness of hedging were applied to in-sample, as well as out-of-sample data over one, five and twenty day hedging periods. These different hedging periods represent daily, weekly and monthly investment horizons, in line with Lien and Tse's (1998) indication that hedging effectiveness differs over different hedging periods.


6.2. STANDARD DEVIATION ANALYSIS FOR HEDGING EFFECTIVENESS

The first method applied to compare effectiveness of hedging, initially proposed by Ederington (1979), is the most widespread method of comparing hedging effectiveness. The standard deviation is used as a measure of volatility. Table 12 presents the standard deviation reduction of the various hedging methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>h*</th>
<th>1-day</th>
<th>5-day</th>
<th>20-day</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.98410</td>
<td>79.59904%</td>
<td>86.74844%</td>
<td>88.93446%</td>
</tr>
<tr>
<td>VAR</td>
<td>0.98852</td>
<td>79.59431%</td>
<td>86.71906%</td>
<td>88.99243%</td>
</tr>
<tr>
<td>VECM</td>
<td>0.99812</td>
<td>79.55142%</td>
<td>86.60357%</td>
<td>89.05879%</td>
</tr>
<tr>
<td>MGARCH</td>
<td>Varying</td>
<td>78.72757%</td>
<td>87.38314%</td>
<td>90.16372%</td>
</tr>
</tbody>
</table>

As the results in Table 12 depict, for in-sample data, the SEMOLS is the most effective method for daily hedging, however over longer periods the Multivariate GARCH method is the most effective method. The VEC and VECM are less effective than the GARCH over five and twenty day periods but more effective over one day hedging periods.

Table 13 presents the standard deviation reduction of the four methods on out-of-sample data.
TABLE 13: STANDARD DEVIATION REDUCTION FOR OUT-OF-SAMPLE DATA

<table>
<thead>
<tr>
<th>Method</th>
<th>h*</th>
<th>1-day</th>
<th>5-day</th>
<th>20-day</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.98410</td>
<td>-82.54518%</td>
<td>-92.96104%</td>
<td>-83.96404%</td>
</tr>
<tr>
<td>VAR</td>
<td>0.98852</td>
<td>-82.46830%</td>
<td>-92.76903%</td>
<td>-84.13091%</td>
</tr>
<tr>
<td>VECM</td>
<td>0.99812</td>
<td>-82.26191%</td>
<td>-92.27263%</td>
<td>-84.46210%</td>
</tr>
<tr>
<td>MGARCH</td>
<td>Varying</td>
<td>-82.45123%</td>
<td>-93.23514%</td>
<td>-82.07718%</td>
</tr>
</tbody>
</table>

The results in Table 13 indicate that over a one-day hedging period, the SEMOLS is the most effective, the Multivariate GARCH is most effective over a five day hedging period and the VECM is most effective over a twenty day hedging period.

However, it is important to note that all the methods provide in excess of 80% variance reduction, which is rather high; therefore, most investors should be willing to apply all the methods to hedge their exposure.

Based on the empirical data, the Multivariate GARCH method is best applied over hedging periods longer than one day and the Single Equation Method is best applied over a one-day hedging period.

6.3. COEFFICIENT OF VARIATION ANALYSIS FOR HEDGING EFFECTIVENESS

The second method applied to compare the effectiveness of hedging is the coefficient of variation. Table 14 presents the in-sample coefficients of variation for the various hedging methods.

TABLE 14: COEFFICIENTS OF VARIATION FOR IN-SAMPLE DATA

<table>
<thead>
<tr>
<th>Method</th>
<th>h*</th>
<th>1-day</th>
<th>5-day</th>
<th>20-day</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.98410</td>
<td>19131.95537%</td>
<td>4822.81008%</td>
<td>4212.17829%</td>
</tr>
<tr>
<td>VAR</td>
<td>0.98852</td>
<td>19560.24253%</td>
<td>4930.30894%</td>
<td>4143.04740%</td>
</tr>
<tr>
<td>VECM</td>
<td>0.99812</td>
<td>20594.05205%</td>
<td>5199.82240%</td>
<td>4019.80613%</td>
</tr>
<tr>
<td>MGARCH</td>
<td>Varying</td>
<td>-165237.30023%</td>
<td>1605.16936%</td>
<td>604.76919%</td>
</tr>
</tbody>
</table>
The smallest coefficient of variation observed for a one-day investment horizon is that of the SEMOLS (the negative coefficient of variation for the MGARCH is not meaningful). However, over five and twenty day hedging periods the MGARCH is the most effective method. These results are in line with the results from the standard deviation reduction analysis for in-sample data.

Table 15 presents the coefficients of variation for out-of-sample data.

### TABLE 15: COEFFICIENTS OF VARIATION FOR OUT-OF-SAMPLE DATA

<table>
<thead>
<tr>
<th>Method</th>
<th>h*</th>
<th>1-day</th>
<th>5-day</th>
<th>20-day</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.98410</td>
<td>-3599.16166%</td>
<td>776.28764%</td>
<td>7158.59483%</td>
</tr>
<tr>
<td>VAR</td>
<td>0.98852</td>
<td>-3691.12724%</td>
<td>776.23820%</td>
<td>5820.69080%</td>
</tr>
<tr>
<td>VECM</td>
<td>0.99812</td>
<td>-3913.91754%</td>
<td>784.10662%</td>
<td>4105.68178%</td>
</tr>
<tr>
<td>MGARCH</td>
<td>Varying</td>
<td>-9692.05959%</td>
<td>2329.00061%</td>
<td>-2707.10778%</td>
</tr>
</tbody>
</table>

According to results in Table 15, no meaningful comparison of hedging effectiveness can be made for one-day hedging periods due to negative coefficients of variation that are not meaningful. Over a five day hedging period the VAR is the most effective method. Over a twenty day hedging period the VECM is the most effective method.

The coefficient of variation analysis neither validates the outcomes of the standard deviation analysis for out-of-sample data nor does it identify one method that is generally superior over the various hedging periods.
6.4. **Risk-Aversion Based Utility Maximisation Analysis for Hedging Effectiveness.**

The final method for comparing hedging effectiveness is the risk aversion based utility maximisation analysis. Table 16, Table 17, and Table 18 present the risk aversion based utility of the various methods over one, five and twenty day hedging periods for in-sample data.

**TABLE 16: UTILITY COMPARISON OVER A ONE-DAY PERIOD FOR IN-SAMPLE DATA**

<table>
<thead>
<tr>
<th>φ</th>
<th>Un-hedged</th>
<th>OLS</th>
<th>VAR</th>
<th>VECM</th>
<th>DVECH GARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>0.00010</td>
<td>0.00002</td>
<td>0.00002</td>
<td>0.00002</td>
<td>0.00000</td>
</tr>
<tr>
<td>0.50</td>
<td>0.000053</td>
<td>0.00002</td>
<td>0.00002</td>
<td>0.00001</td>
<td>-0.00001</td>
</tr>
<tr>
<td>0.01</td>
<td>0.00011</td>
<td>0.00002</td>
<td>0.00002</td>
<td>0.00002</td>
<td>0.00000</td>
</tr>
<tr>
<td>1.50</td>
<td>-0.00014</td>
<td>0.00001</td>
<td>0.00001</td>
<td>0.00001</td>
<td>-0.00001</td>
</tr>
<tr>
<td>2.00</td>
<td>-0.00023</td>
<td>0.00001</td>
<td>0.00000</td>
<td>0.00000</td>
<td>-0.00002</td>
</tr>
<tr>
<td>2.50</td>
<td>-0.00032</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>-0.00002</td>
</tr>
<tr>
<td>3.00</td>
<td>-0.00040</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>-0.00003</td>
</tr>
</tbody>
</table>

Maximum utility for given levels of risk aversion in bold

**TABLE 17: UTILITY COMPARISON OVER A FIVE-DAY PERIOD FOR IN-SAMPLE DATA**

<table>
<thead>
<tr>
<th>φ</th>
<th>Un-hedged</th>
<th>OLS</th>
<th>VAR</th>
<th>VECM</th>
<th>DVECH GARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>0.00051</td>
<td>0.00011</td>
<td>0.00011</td>
<td>0.00010</td>
<td>0.00031</td>
</tr>
<tr>
<td>0.50</td>
<td>0.00019</td>
<td>0.00010</td>
<td>0.00010</td>
<td>0.00010</td>
<td>0.00031</td>
</tr>
<tr>
<td>0.01</td>
<td>0.00058</td>
<td>0.00011</td>
<td>0.00011</td>
<td>0.00010</td>
<td>0.00031</td>
</tr>
<tr>
<td>1.50</td>
<td>-0.00060</td>
<td>0.00009</td>
<td>0.00009</td>
<td>0.00008</td>
<td>0.00030</td>
</tr>
<tr>
<td>2.00</td>
<td>-0.00099</td>
<td>0.00008</td>
<td>0.00008</td>
<td>0.00007</td>
<td>0.00029</td>
</tr>
<tr>
<td>2.50</td>
<td>-0.00138</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00028</td>
</tr>
<tr>
<td>3.00</td>
<td>-0.00178</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00006</td>
<td>0.00028</td>
</tr>
</tbody>
</table>

Maximum utility for given levels of risk aversion in bold
Table 16 indicates that for the given levels of risk aversion, in this study, the Single Equation Method estimated by OLS is most effective strategy over a one-day period for investors with low risk tolerance, investors with higher risk tolerance may prefer not to hedge at all over a one-day investment horizon. This is consistent with the findings for the standard deviation reduction and coefficient of variation analyses for in-sample data.

Table 17 indicates that for the given levels of risk aversion, in this study, the Multivariate GARCH method is the only hedging strategy preferred to the unhedged strategy over a five-day period for investors with varying levels of risk tolerance. Investors with high levels risk tolerance may prefer not to hedge at all. This is consistent with the findings for the standard deviation reduction and coefficient of variation analyses for in-sample data.

Table 18 indicates that, in this study, for the given levels of risk aversion the Multivariate GARCH strategy is the most effective hedging method over a twenty-day period for in-sample data. This is consistent with the findings of the standard deviation reduction and coefficient of variation analyses for in-sample data.

Table 19, Table 20 and Table 21 present the risk aversion based utility of the various methods over one, five and twenty day hedging periods for in-sample data.
Table 19 indicates that for the given levels of risk aversion, in this study, the Multivariate GARCH strategy is the most effective hedging method over a one-day period for out-of-sample data. This is inconsistent with the findings of the standard deviation reduction and coefficient of variation analyses for out-of-sample data.
Table 20 indicates that, in this study, for the given levels of risk aversion the VECM strategy is the most effective hedging method over a five-day period for in-sample data. This is inconsistent with the coefficient of variation and standard deviation reduction analysis for out-of-sample data.

Table 21 indicates that for the given levels of risk aversion, in this study, the VECM strategy is the most effective hedging method over a twenty-day period for in-sample data. This is consistent with the findings of the coefficient of variation analysis and consistent with the standard deviation reduction analysis for out-of-sample data.

It is important to note that investors with different levels of risk aversion may rank the effectiveness of the four methods differently, as their utility functions may differ.
CHAPTER SEVEN: CONCLUSION

This study provides a comparative assessment of the effectiveness of various hedging methods in the South African equities market during the crisis period of 2008-2010. It assesses the effectiveness of hedging by the degree of standard deviation reduction, the minimisation of the coefficient of variation, and the maximisation of utility.

Studies on the optimal hedge ratio have evolved from using the Single Equation Method, estimated by OLS (SEMOLS), to more advanced methods that address the Single Equation Method’s shortcomings. The shortcomings addressed by Vector Autoregression (VAR) model include endogeneity of the variables and serial correlation. The VAR, however, does not address cointegration that is often present in financial time series. Thus, the Vector Error-Correction (VECM) is used to deal with cointegration. The first three methods highlighted above, in the evolution of studies on the optimal hedge ratio, do not take into account ARCH effects that are prevalent in financial time series. Multivariate GARCH methods address the challenge of ARCH effects. Studies on the optimal hedge ratio have evolved to cover a variety of methods. This study applies four such methods: the SEMOLS, the VAR method, a VECM with a VAR base, and a DVEC Multivariate GARCH method.

The evolution of studies on the optimal hedge ratio led to the application of the above stated methods in emerging markets. However, the numbers of studies on the optimal hedge ratio for stock index futures in emerging markets are limited. This study is part of a contemporary set of studies that explore the application of the optimal hedge ratio in emerging markets. Furthermore, the evolution of studies on the optimal hedge ratio has also led to more advanced assessments of hedging effectiveness. This study continues in this vein by applying three methods to assess hedging effectiveness, particularly, standard deviation reduction, coefficient of variation minimisation, and risk aversion based utility maximisation. This assessment of hedging effectiveness compares the four
econometric estimation methods applied in this study to estimate the optimal hedge ratio in the South African equity market.

The data applied in this study is daily closing spot prices for the FTSE/JSE. All Share Top 40 index (ALSI Top 40) traded on the Johannesburg Stock Exchange (JSE), as well as daily closing prices for the ALSI Top 40 future with the nearest maturity, traded on the South African Futures Exchange (SAFEX). The data period ranges from the 2nd of January 2008 to the 31st of December 2010 for in-sample data. Out-of-sample data covers sample data from the 3rd of January 2011 to 15th of June 2011.

The empirical results indicate there is not one econometric hedging method that is persistently the most effective but rather that the most effective method is a function of the hedging period. The SEMOLS is generally more effective over a one-day hedging period and the VECM and Multivariate GARCH are effective over five and twenty day hedging periods. This is likely explained by the SEMOLS ineffectual response to the dynamic nature of stock and futures returns over hedging periods longer than one day. The VAR method for this sample is the least effective method, regardless of the hedging period.

This study represents a step in investigating the effectiveness of hedging in South African equity markets. There remains scope for continued research to expand on the works of this study. In particular, the use of other methods to assess hedging effectiveness in South Africa and other emerging markets and the currency effects for international investors investing in emerging markets. Further investigation into the aforementioned areas would contribute to effective management of the risks associated with investing in emerging equity markets.
LIST OF REFERENCES


