UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL SCIENCES
SCHOOL OF MANAGEMENT

THE HEDGING EFFECTIVENESS OF FUTURES MARKETS: Evidence from Commodity and Stock Markets

Idries Omran Moftah Alghazali

A Thesis Submitted in Partial Fulfilment of Requirements for The Degree of Doctor of Philosophy

Faculty of Social Sciences
School of Management

December 2002

This work is dedicated to the memory of my
Dear loving mother and my special father bless him...

Acknowledgements.

First, I would like to pay my upmost gratitude and thanks to both my supervisors, Dr Taufiq Choudhry and Dr Owain ap Gwilym for the continual encouragement, support, guidance and patience they had given me throughout the duration of my PhD. Secondly I would like to thank Professor Charles Sutcliffe and the Economics Department's teaching staff for allowing me to attend some of the courses related to my topic. I sincerely thank the Engineer Abrahim Ali for his support and encouragement and for making this work possible. I also would like to thank the teaching and administrative staff at the School of Management and the Economic Department, University of Southampton for the help they showed me.

I am indebted to The Great Jamahiria for granting me the opportunity to study for PhD degree in Finance in Great Britain. I also regard myself fortunate and will be forever grateful to my parents and my brothers Abel Qadir and Goma and their families for all the support and encouragement that they have given me. Special thanks to my brother Salem for his understanding support and encouragement. I also thank my special friends Ammar, Bhari, Marai, Mohamed and Sa'ad for never forgotten me, I thank you guys for listening and for the light-hearted comments, you made the whole process bearable and worthwhile. Special thanks also go to all my relatives and friends in Libya and Britain.

I sincerely appreciate and thank all my friends and colleagues from the School of Management. I also thank my friends from the Postgraduate Faculty Research Training Scheme (FRTS, 1999), Faculty of Social Sciences University of Southampton. Guys, it's been an enjoyable ride and experience.

Finally, what a journey!

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF SOCIAL SCIENCES
SCHOOL OF MANAGEMENT

Doctor of Philosophy

THE HEDGING EFFECTIVENESS OF FUTURES MARKETS: Evidence from Commodity and Stock Markets

by Idries Omran Moftah Alghazali

The aim of this study is to investigate the hedging effectiveness of commodity and stock index futures markets. The thesis involves empirical comparison of optimal hedge ratios in stock and commodity futures markets and investigation of whether the short run deviation between cash and futures prices has an effect on hedging. While conducting a comparison between time-varying methods, a comparison is also conducted between the time-varying and the constant methods to identify the effectiveness of each method involved. The empirical investigation is conducted by comparing the risk reducing ability of several different versions of hedge ratios.

Two main methods of estimating the optimal hedge ratios are used. The first method involves constant hedge ratios, where the approaches are unhedged, traditional one-to-one hedge, and minimum variance hedge ratios. The second method involves estimating time varying hedge ratios by means of two approaches: the bivariate GARCH and bivariate GARCH with cointegration (also known as the GARCH-X model). The commodity markets consist of five different series, while the stock index futures cover seven major developed stock markets in different countries. The commodity and stock markets use daily data for within-sample and two out-of-sample time periods. Cash and futures prices are tested for unit roots and cointegration.

According to Fortune (1989) risk transfer and price discovery also take place in the absence of futures markets but these two factors are enhanced in the presence of futures markets. This occurs because the costs of futures transactions are considerably less than the cost of cash transactions. The five different approaches above are compared for their hedging effectiveness in enhancing the ability of investors to reduce risk and enhance price discovery. The comparison indicates whether the time-varying hedge ratios outperform the constant hedge ratio methods. The investor should hedge with the appropriate hedging strategy using the percentage change in portfolio variance as a guiding metric. The percentage change in portfolio variance indicates the reduction of the risk which affects and guides the investment in futures markets. Portfolio managers may hedge using the time-varying hedging methods when compared to the unhedged and traditional methods, as the reduction in variances are

more substantial. However, they may hedge risk using the minimum variance method for commodity and stock markets where the drop in the variance using time-varying methods is small, because transaction costs may exceed the benefits. The trade off between the transaction costs and risk reduction is analysed in order to determine the practicality of the time-varying hedge methods. This provides a further contribution in the thesis, incorporating Park and Switzer's (1995) views of the necessity for less frequent re-balancing of the hedge portfolio in following the changing optimal hedge ratio.

Evidence presented in this study indicates that the hedging strategy using the time-varying hedge ratio is potentially more effective than the constant hedge ratios for the stock markets, but may not be the case for the commodity markets. For the stock markets, the comparisons reveal that the dynamic strategy based on the bivariate GARCH and GARCH-X methods improve the hedging performance considerably over the unhedged and traditional hedging strategy, while marginally improving the hedging strategy performance in some cases in comparison to the minimum variance hedge methods. The reduction of risk exists for the time-varying methods in most cases, however, this modest risk reduction may not compensate for the transaction costs. A further contribution is the evidence that incorporating the short run deviation between cash and futures prices has an impact on the hedging effectiveness in some cases but not all for both the stock and the commodity markets.

The relative performance of the time-varying hedge ratios based on both GARCH and GARCH-X methods is better for the out-of-sample time periods. Reducing the length of the out-of-sample period improves the performance of the time-varying hedge ratios. For the stock index futures markets, these methods generally under-perform for within-sample data compared to the minimum variance hedge. For the commodity markets, time-varying hedge ratios under-perform in most cases compared to the minimum variance method for both within-sample and out-of-sample time periods.

Empirical investigation of time-varying hedging with transactions costs is conducted. The hedging effectiveness for the out-of-sample time period is conducted between the minimum variance, GARCH and GARCH-X methods. The hedge efficiency varies considerably from one case to another. The cases where the percentage change in variance are small under-perform in comparison to the minimum variance when transaction costs are introduced. The smaller the percentage reduction in variance achieved by time-varying hedging, the less likely that this will be sufficient to cover transaction costs. This is evident for the GARCH-X model, which is not convincingly superior to the constant minimum variance hedge. The overall conclusion is that time-varying hedging is often inferior to the constant minimum variance hedge when transaction costs are taken into consideration. This is more evident in the commodity markets than the stock markets.

TABLE OF CONTENTS.

LIST OF TABLES

LIST OF FIGURES.

CHAPTER ONE

1.0 INTRODUCTION.

The last few decades of the Twentieth century are remembered as a time of unprecedented financial innovation augmented by significant improvements in data processing technology and sophisticated international communication links. The same period has been characterised by uncertainty and financial market volatility of a previously inconceivable magnitude largely due to increased financial risk. Prior to the 1970s, futures contracts existed only for agriculture, energy and metal markets, however due to the extraordinary growth and the exceptional volatility in inflation, interest rates and exchange rates, an explosive growth in financial futures occurred in the form of interest rate futures, stock index futures and foreign currencies futures. In this economic environment, financial investors and market professionals have demanded hedging instruments which are viable, flexible, and immediately available. Financial futures exhibit these features, and hedging strategies may be used to assist in the management of risk in an investment portfolio.

Hedging is claimed to be of fundamental importance in managing the risk of an investment portfolio and is arguably the major justification for the existence of futures contracts (Holmes, 1996). The objectives of hedging are to reduce or to eliminate the risk of price fluctuations along with price certainty of the investment. In theory and in the absence of natural hedges, hedging is generally encouraged as a valuable activity for investors to engage in. However, hedging is not a costless activity. Apart from the direct costs associated with the hedging instruments such as transaction costs which comprise adverse price movement, commission, the opportunity cost of the funds, and taxes, there are also indirect costs such as the costs of management and monitoring of the hedge position, specification risk and basis risk. These costs need to be weighted against the benefits of the hedge when deciding to enter into a hedging strategy.

This dissertation examines the effectiveness of alternative hedge ratios in stock and commodity futures markets and considers whether the short run deviation between cash and futures prices has an effect on the optimal hedge ratio. This study investigates and compares the performance of the time-varying hedge ratio method of Generalised AutoRegressive Conditional Heteroscedasticity (GARCH) and GARCH with Cointegration (GARCH-X), with the aim of identifying the most efficient method to estimate the optimal hedge ratio for futures markets. The original contribution is to investigate whether the short-run deviation between cash and futures prices has an impact on the hedge effectiveness.

A variety of techniques to assess the effectiveness of a hedge have been suggested in the literature. In this study an empirical investigation and comparison of four hedging methods plus the unhedged method have been undertaken. The methods investigated consist of both constant and time-varying hedge ratios. The study is of practical importance given the need for investment managers to determine the effectiveness of hedging activities, and adjust their strategies accordingly. Hedging is a widely accepted practice that is assumed to be a valuable activity but its value can only be assessed by empirically analysing the effectiveness of the hedge in reducing risk, which is regarded as the aim of this thesis.

The theme of the thesis focusses on whether using the time-varying joint distribution of cash and futures prices is appropriate to estimate the optimal hedge ratios for commodity and stock index futures series. The thesis also investigates whether the short run deviations from the long run relationship between cash and futures prices have any effect on the time-varying optimal hedge ratio. The thesis also presents the most effective method through comparison of the change in the portfolio variance. Evidence presented in this study indicates that the hedging strategy using the time-varying hedge ratio is potentially more effective than the constant hedge ratios for the stock markets, but may not be the case for the commodity markets. A further contribution of the thesis is to identify the most practical hedging method applied. An alternative strategy of less frequent re-balancing of the portfolio is considered as suggested by Park and Switzer (1995). The thesis presents an original and unique investigation of the trade off between risk reduction and transaction costs, which gives practical insights for selecting a suitable hedging strategy.

The hedge methods examined in this study are the constant methods in the form of the traditional method and the minimum variance method, while, the time-varying methods include the bivariate Generalised Autoregressive Conditional Heteroscedasticity method (GARCH) and the augmented GARCH method (GARCH-X). These methods are analysed within the context of hedging the underlying market risk using stock and commodity futures contracts. Daily stock market data is utilised from seven major markets: Australia, Germany, Hong Kong, Japan, South Africa, UK and the USA. Daily data from the commodity futures markets comprises of one Agriculture (Cocoa), one Metal (Aluminium) and three Oil, namely West Texas Intermediate (O1), Brent Crude (O2) and Gas Oil EEC (O3). For the stock index futures markets, the within-sample time period applied is 1st January 1991 to 31st December 1999 and then this time period is broken up into two out of sample time periods; a one year time period (1st January 1999 - 31st December 1999) and a two year time period (1st January 1998 - 31st December 1999). Meanwhile, for the commodity futures data, the within sample time period applied is 1st January 1990 to 31st December 2000. This period is also broken up into one year (1st January 2000 - 31st December 2000) and two year out of sample time periods (1st January 1999 - 31st December 2000).

Out-of-sample results may provide improved hedging effectiveness by comparing the one and two years periods to each other and to the within-sample time period results using the constant and time-varying methods. The effectiveness of the hedge ratios are investigated by comparing the variance of different method's portfolios for within-sample periods and the out-of-sample performance. The portfolio variance associated with each method must be detected in order to identify an optimal portfolio to analyse risk. The length of the out-of-sample periods are selected in order to investigate whether changing the length of the time period has any affect on the results and whether reducing the time period length of the out-of-sample period improves the performance of the time-varying hedge ratios. The hedge efficiency of selected cases is investigated. From the out-of-sample results in the stock and commodity futures markets, the series where the time-varying hedge ratio out-perform the constant minimum variance are identified using the percentage change in variance and then an empirical insight into time-varying hedge with transactions costs is thoroughly conducted in chapter 7.

Prior to estimation of the hedge ratios using the conventional and time-varying methods, one needs to examine the stochastic structure of the data involved. Tests for stationarity are conducted using Augmented Dickey-Fuller (ADF) and the KPSS tests. The one root is testing for trend stationarity, and the two roots is testing for stationarity around the mean. The KPSS tests are intended to complement the ADF unit root tests. In order to apply the GARCH-X model, we need to test for cointegration between the cash and futures prices. The cointegration between cash and futures prices is estimated by using both the Engle-Granger (1987) and the Phillips and Hansen (1990) models. If the index futures and cash levels series are cointegrated, an error correction term is applied to the standard bivariate GARCH model. This model is called the GARCH-X model which may be used to investigate the impact of short run deviations from the long run relationship between cash and futures prices upon hedge ratios.

The structure of thesis comprises the following: Chapter 2 discuses the theoretical framework for hedging with futures. This chapter starts with an overview of futures markets and it is then divided into two main sections. The first section looks at the development and organisation of futures markets and the second discusses trading in these markets with special attention given to hedging and the hedge ratio as the focal points of this research. Chapter 3 analyses the relevant research literature which provides the background for the empirical analysis for both commodity and stock index futures markets. The research methodology is presented in chapter 4. This chapter explains and discusses the tests along with explanations of the constant and time varying methods. The empirical results are provided in chapters 5 to 7. In chapter 5, the data, results and analyses for the stock index futures markets are investigated in two main sections. The first section presents the within-sample results and the second section presents the out-of-sample results. Chapter 6 is entirely devoted to results and analyses based on the commodity futures markets. This chapter evaluates five commodity market strategies to manage price risk. Results in this chapter are also presented in two sections, similar to chapter 5. The sections are concerned with the estimation and analyses of optimal hedge ratios on futures markets and provide detailed discussion of data for the commodity and stock index futures markets under study focussing on hedging effectiveness for within and out-of-sample time periods. Chapter 7 presents empirical insights into time-varying hedging with transaction costs. It presents direct evidence of the practical usefulness of different hedging methods given the trade-off between risk reduction and transaction costs. Finally, chapter 8 concludes the study and discusses the implications of the findings.

CHAPTER TWO

2.0 HEDGING WITH FUTURES.

Hedging with futures signifies taking a position in futures contract(s) that offsets some of the risk associated with some given market commitment. Futures contracts are derivative instruments in the sense that they derive their value from the price behaviour of the underlying cash market[1]. From the simplest perspective, a futures contract is a legally binding agreement between two parties in which they agree to exchange the underlying asset for a pre-specified price at a future date. It delivers a pre-specified amount of a particular commodity, cash instrument or its cash equivalent on a given future date, and at a pre-agreed price. The success of futures markets is undeniable. This success is largely attributed to the fact that futures markets are considered effective in hedging the market risk of well diversified portfolios. They facilitate trading in one single transaction to hedge against market risk.

Futures markets and their application as risk management and trading tools have grown dramatically since their inception. This rapid growth of futures markets continues to include different types of markets such as traditional and financial futures markets. The traditional futures markets consist of agricultural commodities, energy, and metal markets, while the financial futures markets include interest rate futures, stock market indices, and foreign currencies futures markets. In this thesis, the traditional markets consist of three energy (Oil) markets, one metal (Aluminium) market and one agriculture (Cocoa) market, while for the financial markets, the stock index markets were the focus in this particular research. Seven major stock index futures markets were chosen from developed countries, namely Australia, Germany, Hong Kong, Japan, South Africa, UK and the USA. The objectives of these markets are the reduction or elimination of the risk of price fluctuations along with price discovery.

---

[1]Sutcliffe (1997) states that in commodities markets the term 'cash market' is used to refer to the market in a particular grade and location of the underlying asset. For index futures there is only one underlying grade and location. And so the cash market is synonymous with the spot market.

2.1 DEVELOPMENT OF FUTURES MARKETS.

The transformation of international financial trading has been most noticeable in recent years. The trend of deregulation of financial control and the internationalisation of capital movement have dramatically increased the volume of financial futures contracts traded in major financial centres. Financial futures are now recognised and employed by financial institutions, corporates and private investors alike, and have established the futures industry as both sophisticated and innovative. Meanwhile, phenomenal growth has been observed both in terms of new types of contracts and number and types of participants. Futures markets and their application as risk management and trading tools have grown dramatically since their inception. The trading activity of these contracts well surpasses the total trading volume and open positions of the underlying cash markets themselves.

What are the reasons for the success of futures markets?. As mentioned earlier, in cash markets commodity delivery and payment is made instantly. However, if the buyers are in need of the commodity in the future instead of immediate need, then, they were given three choices: first was to buy the commodities now and store them until required in the future; second was to wait until needed then buy them from the cash market; and the third choice was to deal in the futures markets. Dealing in the futures markets starts by buying the commodities now for delivery at a later date when required. The cost and risks for the three different situations vary. In the first, the buyer had to carry the storage costs and in the second the risk involved changing of prices. However, in the third, dealing in the futures markets, there are no storage costs and the risk associated with change in price is reduced or disappears completely. It became obvious that the main advantage for the appearance of the futures markets is avoiding or reducing the risk of price changes.

Even though futures markets have grown dramatically in the last thirty years of the Twentieth century, the history of the futures market goes far back. Futures markets in their modern form were found in the United States city of Chicago in the mid-nineteenth century. Chicago has the reputation of being the largest centre of futures trading and is the birthplace of financial futures contracts. The Chicago Board of Trade (CBOT), established in 1848, was the first active exchange for trade of agriculture commodities, especially grain. Following the continuing success of commodity futures contracts, it was recognised that the theories of agriculture commodity futures trading could be applied to the commodity of money. Financial futures contracts were first introduced in the 1970s in the United States. The Chicago International Money Market (IMM), a division of the Chicago Mercantile Exchange (CME), launched currency futures trading in 1972 and interest rate futures were introduced in 1975. The CME launched stock index futures in 1980. In their short history of trading, stock index futures have had a great impact on the world's security markets. Their existence has revolutionised the art and science of equity portfolio management. Holders of fixed positions in equity portfolios attempt to track the performance of broad market indices. The objective of such actions is the optimal diversification of risk inherent in holding investment portfolios. Stock index futures, as they are derivatives on stock indices, are an alternative means of tracking market wide movements. Their advantages over trading are important to understand. Such advantages can be easy short selling, low transactions costs, high leverage, liquid market, taxation regulations, and longer trading hours.

Stock index futures are an effective hedging instrument which explains their increasing popularity since their inception. They offer a number of attractive possibilities for improving risk management and for enhancing returns in equity investments. Hedging with stock index futures also involves features which are unique to the stock market. A stock index future is a bet on the value of the underlying index at a specified future date which gives the owner the right and the obligation to buy or sell the portfolio of stocks characterised by the futures index.

In the maze of existing futures contracts and the potential possibilities in futures markets we can clearly distinguish between commodity futures, irrespective of what the underlying goods may be, and financial futures. The possibilities in the commodity futures markets are immense. However, traditionally these markets are in agricultural commodities, energy and metals. Financial futures can be classified into three main groups: foreign currency futures, interest rate futures and stock index futures. Financial futures and commodity futures differ in several respects. These differences are concerned with matters such as storage costs, seasonality, physical delivery and manipulation. Futures markets do not exist in every commodity market, but many transactions that involve an agreement now to buy or sell something in the future do take place.

Such transactions are termed forward transaction. A futures contract is very similar to a forward contract but there are some important differences. The most important difference is that futures contracts are designed to be traded. For this to be possible there must be a standardised contract with respect to the designated quantity or contract size, quality, delivery date, delivery location and counter party (the clearing house) as well as a well-organised futures market which enables and ensures trading in these contracts. Viability, liquidity and reliability allow market participants to trade freely and easily on the exchange with precise knowledge of the contracts being traded. It is these basic features of futures contracts supported by the mechanics of the futures markets which enable market participants to take advantage of or to alter their risks in the face of adverse, unexpected price changes. In contrast, forward contracts are "one-off" agreements tailor-made to meet the requirement of the two counter parties involved in terms both of the size of the transaction and date of delivery.

Hedging with stock index futures will normally involve selling futures against a long position in a stock portfolio. The effect on portfolio risk and return will depend on the hedge proportion and on the composition of the portfolio being hedged. A perfect hedge however in this case is almost impossible as the cash asset is not identical to the market index, basis risk will remain, and therefore total risk is not reduced to zero. Several issues of practical importance concern the futures contract. The hedger must choose the futures contract to be used in the hedge as well as the particular delivery date. The choice of the futures contract on the one hand is determined by the extent to which the price movements on the cash position are correlated to those of the futures contracts. Furthermore because basis risk is thought to decline as delivery approaches, the risk of the hedge may be minimised by using the contract with the closest delivery date to the planned horizon date.

According to Shalen (1989) risk is reduced for three reasons: the higher risk minimising hedge ratio, the lower interest rate, and dividend risk. Should the hedge extend after the nearby contract expires then the position can be rolled over to the next futures contracts. In some cases, it is more convenient to take a position initially in the following contract to deliver thus eliminating the need to roll over the hedge. This is best because of the maturity effect. As the contract approaches delivery, the volatility of its price will increase partly due to the fact that the amount of futures traded is largest close to maturity. Meanwhile, mis-pricing of futures prices have important implications for hedging cash market positions. The existence of mis-pricing affects initial hedge ratio selection, hedging effectiveness and the expected cost of hedging.

A stock index futures hedge is an act that reduces the price risk of an existing or anticipated position in the cash market, under the assumption that a portfolio of common stock is being hedged. One of the objectives of hedging is to transfer risk from one to another individual or corporation. The person off-loading the risk is the hedger, while the person taking on the risk is the speculator or trader. Hedgers are concerned with the adverse movements in security prices or increases in volatility which increase the overall riskiness of their position. For example, if an individual has a long position in cash market securities, he/she will be concerned about the prices of those securities falling and will want to protect against this possibility. Alternatively, if an individual has a short position in cash market securities, he/she will be concerned about rising prices and will want to protect against this possibility. Duffie (1989) defined the futures position as the cumulative total to date of the number of contracts purchased less than the number of contracts sold.

In order to hedge successfully, a suitable hedging instrument will have to be selected, namely one whose price movements mirror closely those of the underlying security. The most suitable hedging instruments will therefore be instruments that are derivative upon the cash market security. Futures contracts more than fulfil this role and are used to hedge interest rate risk, currency risk and market risk. Futures contracts serve as a hedge when a position is taken in futures that is opposite to that of the existing or the anticipated cash position. In other words, hedgers sell futures when they are long in the cash asset and buy futures when they are short in the cash asset. As gains in the futures markets offset losses in the cash market, the variability of returns is lower than that of the unhedged position. Ideally, every hedge would perfectly reflect the differences in price volatility between the two instruments, so that as prices change, the loss in the cash position would be offset exactly by profit on the hedge position. However, this situation assumes a direct hedge or a hedge in which the hedging instrument is established in such a way that its price movements are perfectly negatively correlated with those of the underlying cash market. Most hedges are partial or cross hedges which is the situation when the cash asset and the asset underlying the futures contract are not identical. Nearly every use of stock index futures involves a cross hedge, therefore, hedgers use the futures contract whose price has the highest correlation with the cash price of the asset concerned.

The price relationship between the cash instrument and the hedge instrument is known as the "basis". The basis is the difference between the futures price and that of the underlying asset ($B = F - S$), the B is the basis, F is the current future price and S is the current cash price[2]. There will be a different basis for each delivery month and for each contract. Before delivery date the futures price could be above or below the cash price. A positive basis situation is known as contango and was first introduced by Keynes (1930). Keynes pointed out on the price interrelationship of forward and cash prices in organised markets where redundant stocks of an underlying asset exist, it would be in the interest of investors to sell the stocks cash and buy them back forward rather than incur carrying costs for the intervening period. The existence of surplus stocks must cause the forward price to rise above the cash price, to establish a contango. This contango must be equal to the carrying costs. The inverse interpretation is valid when the futures price is less than the cash price, thus the basis is negative. This situation is known as backwardation. In terms of Keynes' outlook, given that no arbitrary condition is used to derive the futures price held, the basis for stock index futures is positive ($F>S$) since it is the liquidity of the shares composing the underlying index that is questionable rather than the futures contract itself. As maturity approaches, the size of the basis, whether positive or negative, decreases tending toward zero, where at maturity it is zero. The process of the basis moving to zero is called convergence. For the convergence process, the basis tends to zero because the carrying charges tend to zero as the contract approaches delivery. In consequence at delivery $F=S$ and the basis is zero.

[2]Some markets define the basis as the cash price minus the futures price.

2.2 HEDGING STRATEGIES.

There are two fundamental trading strategies, known as hedging and speculation practised in futures markets. Hedging is taking a position in two or more securities that are negatively correlated (taking opposite trading position) to reduce risk. It is a protection of an open position to minimise risk (by seeking price certainty and speculating that derivative prices will move the other way as well, to try and cover potential losses). A position where this has not been done is called unhedged position, and this is a riskier position to maintain (Leeson, 1996). Hedging in futures markets is regarded as the deals that are carried out by investors and executed in the future limiting the losses facing investors. If hedging protects the hedger then the hedging costs appear as the difference between hedging and unhedged cashflow.

There are three different kinds of hedging: perfectly hedged position, long (buy) hedge, and short (sell) hedge. First, a perfect hedge is one that completely eliminates the risk. The objective of futures markets to hedge a risk is to take a position that neutralizes the risk as far as possible. In other words, a perfect hedge position means that the hedger owns the long and short contracts with the same price and quantity and for the same delivery date, and thus will not be exposed to any losses due to changes of prices.

Second, long (buy) hedge means buying a contract on futures markets to protect against the risk of price change. Long hedge may also be used to partially off-set an existing short position. Consider an investor who has a short stock, where part of the risk faced by the investor is related to the performance of the stock market as a whole. The investor may neutralize this risk by taking a long position in index futures contracts. Assume that the futures position is closed out in the delivery month. The hedge has the same basic effect if delivery is allowed to happen. Delivery is not usually made even if the hedger keeps the futures contract until the delivery month. Hedgers with long position usually avoid any possibility of having to take delivery by closing out their positions before the delivery period. In practice, marking-to-market does have a small effect on the performance of hedge. The pay-off from the futures contract is realised day by day throughout the hedge period rather than at the end.

Finally, short (sell) hedge means that selling futures contract to avoid the risks of decrease of prices in a particular commodity or financial asset. This type of hedging is used by those forced to buy commodities from the spot market for storage for fear of a reduction in prices of the commodity. However, in actual hedging applications, the hedged and hedging position will differ in the time span covered, the amount of the commodity, and the particular characteristics of the goods. In such cases, the hedge will be a cross-hedge which is where the characteristics of the spot and futures positions do not match perfectly. A short hedge is a hedge that involves a short position in futures contracts. A short hedge is appropriate when the hedger already owns or is expected to own an asset and expects to sell it sometime in the future. Cross hedge does not usually occur in commodity and financial futures markets. The seller usually owns the commodity or financial futures with the same condition approved in the contract. In this situation, the commodity or financial futures could be replaced at the execution date by other commodity or financial futures. However, this could be used as a base to hedge a contract of some other commodity or financial futures.

2.3 SPECULATION STRATEGY.

There is not much difference between the motives of speculation and hedging involving the concept of returns and risks. In each case the objectives are to reduce risk and remain on the same return, or increase return and remain on the same level of risks. The speculation in futures markets aims to invest in different kinds of futures such as stocks, interest rates and currencies. According to Sutcliffe (1997) speculation defined as trading on anticipated price changes, where the trader does not hold another position which will offset any such price movements.

In a world of uncertainty, speculation refers to transactions where expected capital gains provide a major motive. Speculators may buy goods or assets they do not want but whose prices they expect to rise. They can contract to buy assets they do not have the funds to pay for or to contract to sell assets one does not actually posses. First, the speculator decides which assets to deal in, then he/she carries out analysis to predict futures prices. These analyses are divided into two types; first is the fundamental analysis which analyses the factors that affect supply and demand. For example, in the commodity case, the supply is influenced by the cultivated land, weather (climate), and storage etc, while the demand is influenced by the population growth, animal growth and the export capabilities. The second kind of analysis is the technical analysis which depends on the study of price movement based on predicting futures prices. According to the technical and fundamental analysis of price movement in the future, the speculator takes a suitable position in futures markets whether it is long or short position.

Speculators tend to take long position on a commodity when the expectations indicate the upward movement of commodity futures price, but taking short position on a commodity when the expectations indicate the downward movement of commodity futures price. If the speculators themselves have unstable expectations, speculation is liable to amplify fluctuations in asset prices due to other causes. Whether speculation tends to stabilize or destabilize markets is controversial.

2.4 THE OBJECTIVE OF HEDGING.

The aim of hedging in futures markets is to reduce a particular risk. This risk might relate to the different kind of markets such as commodity or financial markets. The objectives of futures markets is to hedge a risk by taking a position that neutralizes the risk as far as possible. Such a hedge can be a perfect hedge which is the hedge that completely eliminates the risk. Three distinct theories can be used to measure the hedging effectiveness, these are known as hedging strategies: the risk minimisation approach, the profit maximisation approach, and the portfolio approach (Sutcliffe, 1997). The portfolio approach besides maximising return also has a goal to minimise risk and will therefore be analysed in these terms.

Historically speaking, before the Second World War the concept of hedging was purely one of risk minimisation. Hedging and the avoidance or reduction of the risk of price changes went together, the former being motivated by the demand for the latter. Post-war development in academic literature represents a significant departure from this tradition. However, the change in attitude can not be accounted for by changes in the practice of hedging. In business practice today hedging is still commonly described in terms of the avoidance of price risk.

2.4.1 Risk Minimisation Approach.

The traditional rationale for existence of futures markets is to facilitate hedging and price discovery. The function is defined as the transfer of price change risk from more to less risk averse investors. This is accomplished by matching one risk with an opposing risk and therefore the price movements in one are offset by those in the other. The hedging in one asset results in the cash position reaching equal magnitude to those of the other. This is the classical hedging strategy of a one-to-one hedge ratio. This refers to a traditional hedge where the risk of an additional investment exactly offsets the initial risk and thus eliminates initial risk. In circumstances like these a question arises as to whether futures contracts that are traded can help minimise the overall risk faced.

Criticism on the traditional view of risk minimisation characterises the one-to-one hedge as simple and naive (Anderson and Danthine, 1981), while Ederington (1979) states that it is not only wrong but indicates a lack of sophistication on part of the hedgers who use it. The critics of the traditional view to hedging usually deal with futures in a risk-return portfolio framework and show that a risk minimising hedging ratio need not be the one to be effective. In fact it may well reduce the effectiveness of the hedge. What the two approaches have in common is that both strive to minimise the risk of the overall cash position. Profit maximisation as a motive for hedging is the other extreme.

2.4.2 Profit Maximisation Approach.

It is self evident that anyone hedging a commitment by the sale or purchase of futures contracts, whether this position is or is not equal to the actual commitment, places himself in a position which he/she regards as better than any other course of action open to him/her. Working (1953) points out that the profit maximisation approach implies that traders, processors or manufactures hedge whenever they believe that hedging increases total income. This type of hedging may be termed carrying-charge or arbitrage hedging.

Working (1953) stated that carrying-charge hedging is done in connection with the holding of commodity stocks for direct profit from storage rather than merely to facilitate the operation of a producing or merchandising business. He also pointed out that the main effect of carrying-charge hedging is to transform the operation from one that seeks profit by anticipating changes in the price level to one that seeks profit from anticipating changes in price relation. In other words, the objective of hedging is speculation on the basis. Working recognised several categories of hedging and supported the concept of profit maximisation in terms of the different types of hedging that investors or businessmen engaged in. These categories of hedging are operational hedging, selective hedging, anticipatory hedging and pure risk-avoidance hedging.

2.4.3 Portfolio Theory Approach.

The view that basic portfolio theory can be applied to hedging stems back to the early 1960's and 1970's with Stein (1961), Johnson (1960), and Ederington (1979) being the most important representatives. They were able to integrate the risk avoidance of traditional theory with Working's (1953) expected profit maximisation. They argued that a portfolio approach to hedging is superior to either of the two and that investors buy and sell futures for the same risk-return reasons that they would buy other securities. They also originated the view of hedging that appears to prevail today which draws from portfolio theory. The rationale underlying the theory is that hedgers are risk averse utility of wealth maximisers

The portfolio approach proposes an optimal hedged position that consists of two components: a pure hedge component and a pure speculative component. The hedge component is incorporated as a variance-minimising model associated with the low risk portion of the risk-return spectrum and the speculative component is presented as a utility maximisation model, in which mean return is maximised subject to a constraint on the variance of return. The objective in both the minimum variance or return maximising hedge ratio is to find the optimal hedge ratio.

2.5 HEDGE RATIOS.

Hedging is probably the most important single trading activity in the futures market. Hedging is a strategy to minimise the risk, it is a defensive mechanism, and the financial market should be used to reduce risk not taking the chance to increase the risk. Hedging is all about selling risk you do not want to those willing to take it. Therefore hedging is a beneficial activity involving risk spreading, risk selling, and risk reducing. Some may choose to sell the risk to others who are prepared to take it on, so you can get rid of the risk by insuring your house, your car, etc. Hedging is often viewed as the purchase of insurance, hedgers trade in futures market and speculators bear the risk that the hedgers try to avoid. Naturally, the speculators demand some compensation for this service. The theory of backwardation and contango were considered as explanations of the way in which speculators might receive compensation for bearing risk.

Most trades in futures markets are hedging trades.[3] Hedging if done correctly is a very sensible strategy and is the main use of these markets. However, to start hedging you have to answer the key question of the appropriate hedge ratio. The hedge ratio (β) is usually defined as the number of futures contracts traded per unit of cash securities held. Generally speaking when the hedge ratio is zero the risk and return of the cash position is the same as that of the unhedged position. However, as the hedge ratio increases the hedge improves. The size of the hedge ratio depends on the different theories as to the purpose of hedging even if the objectives are identical.

Consider an investor with a fixed long cash position in a stock or commodity at time t-1, who wishes to hedge some proportion of this cash position in a futures market. The return on holding a portfolio comprised of the underlying asset and futures contracts is defined by:

$$r_t = r_t^c - \beta_{t-1} r_t^f \qquad (2.1)$$

where r_t is the return on holding the portfolio between t-1 and t; r_t^c is the return on holding the cash position between t-1 and t; r_t^f is the return on holding the futures position between t-1 and

[3]For example, see Holland and Vila (1997)

t; and β_{t-1} is the hedge ratio, defined as the value of futures sales at t-1 divided by the value of the cash position at t-1. The negative sign reflects the fact that to hedge a long position in the underlying asset normally it is necessary to sell futures contracts. Similarly, to hedge a short position in the underlying asset, the investor must normally take a long position in index futures contracts. An exception to this will occur when there is negative covariance between cash and futures returns, whereby a long cash position will be off set by a long futures position, while a short cash position will be off set by a short futures position. The variance of the return on the hedged portfolio, conditional on information available at time t-1, is given by

$$Var(r_t/\Omega_{t-1}) = Var(r_t^c/\Omega_{t-1}) + \beta^2_{t-1}\, Var(r_t^f/\Omega_{t-1}) - 2\beta_{t-1}\, Cov(r_t^f, r_t^c/\Omega_{t-1}) \quad (2.2)$$

where Ω_{t-1} is information available last period. $Var(r_t/\Omega_{t-1})$ is the variance of the hedge portfolio, $Var(r_t^c/\Omega_{t-1})$ is the variance of cash returns, and $Var(r_t^f/\Omega_{t-1})$ is the variance of futures returns, while, $Cov(r_t^f, r_t^c/\Omega_{t-1})$ is the covariance between cash and futures returns. The return on a hedged position will normally be exposed to risk caused by unanticipated changes in the relative price between the position being hedged and the futures contract. The hedge ratio that minimises risk may be obtained by taking the first difference with respect to β for the above equation. The hedge ratio β_{t-1} can be expressed as:

$$\beta_{t-1} = Cov(r_t^c, r_t^f/\Omega_{t-1})/Var(r_t^f/\Omega_{t-1}) \quad (2.3)$$

where, $Cov(r_t^c, r_t^f/\Omega_{t-1})$ is the covariance of the returns of the cash and futures portfolios, while $Var(r_t^f/\Omega_{t-1})$ is the variance of return futures. If this covariance is positive, the cash returns and futures returns are moving in the same direction (which is the normal situation), while if the covariance is negative then the cash returns and futures returns are moving in opposite directions. In the latter case, the hedge ratio is negative (consequences of this were discussed above).

The next chapter proceeds to analyse previous empirical work on the effectiveness of different hedging approaches.

CHAPTER THREE

3.0 REVIEW OF LITERATURE.

Futures trading developed as a contribution to the efficiency of a relatively competitive economy. Futures trading emerged as early as 1850 in the grain trading at Chicago, since then new forms of trading followed at other markets. i.e. financial markets and commodity markets. Working (1953) defined futures trading in commodities, as trading conducted under special regulation and conventions, more restrictive than those applied to any other class of commodity transactions. They serve primarily to facilitate hedging and speculation by promoting exceptional convenience and economy of the transactions.

Speculation emerged in futures trading with hedging is seen as an opportunity for risk reduction in the futures markets trading. Since then hedging has become the main tool, and speculation in futures is like a companion going where hedging gives it the opportunity to go. Although the amount of speculation on a futures market seems to depend so much on the volume of hedging, there is also a connection in the other direction. As between different exchanges dealing in the same commodity, there is a strong tendency for hedgers to prefer to use the exchange which has the largest volume of speculative trading. It is apparent that the existence of futures trading relies purely on the basis of desire of people to speculate, but futures trading cannot long persist except on the basis of conditions that create speculative risks which somebody must carry, and which some people are led to transfer to others by hedging.

Earlier on, Working (1953) pointed out that hedging is not a sort of insurance, nor usually undertaken in the expectation that cash and futures prices would rise or fall equally. He also mentioned that hedging is a form of arbitrage, undertaken most commonly in expectation of a favourable change in relation between cash and futures prices. The fact that risks are less with hedging than without is often a secondary consideration. In Working's arbitrage theory, hedging is viewed as an act of arbitrage between cash and futures prices. Hedging positions are placed if the hedger believes that futures prices reflect an attractive profit opportunity when compared to the cash price. What represents an attractive profit opportunity is something that only individual hedgers can decide. The reasons for hedging are so varied that it would be difficult, if not impossible, to come up with a precise form for it that would apply to all hedgers. The important point is that most hedgers are motivated by profit and not by the desire to reduce risk according to Working (1953). This does not mean that hedgers are unconcerned with risk, but rather that reduction refers to profit as the primary motive in undertaking a hedge. Additionally, Working (1953) argues that expectations regarding future events are embedded in cash prices just as they are in futures prices. So much so that, at least for storable commodities, the difference between cash and futures prices (the basis) does not depend on events forecast to occur in the future. Under the assumption that a portfolio of common stock is being hedged, hedgers are concerned with the adverse movements in security price or increase in volatility which increase the overall riskiness of their position.

Given the hedger's degree of risk aversion, the hedger chooses to hedge partially or fully in an attempt to trade-off risk against return. An important results developed from the portfolio theory approach[4] is the concept of the minimum-variance hedge ratio. A hedger initiates a minimum-variance hedge if he/she is extremely risk averse. Although there is no consensus regarding an appropriate method to estimate the minimum-variance hedge ratio, a distinct bias in favour of regression analysis exists. The portfolio view elevates risk reduction to a level of primary importance or to a level of importance equal to that of profit. If futures prices are unbiased, then the portfolio view of hedging reduces to that minimum-variance hedging, thereby giving risk reduction prime consideration in the hedging decision. This contradicts Working's view. If a long position is held in the cash market security then a decrease in prices concerns the hedger who will want to protect himself against this possibility. Alternatively if a short position is held then an increase in prices will spur the hedger to protect himself against this outcome. It is easier to analyse the hedger's position in terms of its hedge ratio (β). Sutcliffe (1997) defined the hedge ratio as the number of futures contracts bought or sold divided by the number of cash contracts whose risk is being hedged. Hedge ratio (β) is also defined mathematically as the conditional covariance between cash futures returns divided by the conditional variance of futures return.

[4]See section 2.4.3 of chapter 2.

3.1 Cash and Futures Market Interaction.

Hedgers historically view hedging in terms of the basis[5]. This is because hedging is seen much more as an act of arbitrage between cash and futures prices rather than as an action undertaken to reduce risk (such views were evident in Working, 1953). Perhaps the main reason that hedging, as commonly practiced on futures markets, has been so widely misunderstood and misrepresented is that economists have tried to deal with it in terms of a concept that seemed to cover all sorts of hedging. This would be desirable if it were feasible, but the general concept of hedging as taking offsetting positions does not apply well to most hedging in futures markets. Working (1953) pointed out that hedging in commodity futures involves the purchases or sales of futures in conjunction with another commitment, usually in the expectation of a favourable change in the relation between cash and futures prices.

The conventional belief of the relationship between a particular cash and futures market is that the futures market should lead the cash market due to greater liquidity and more frequent and easier trading. The following can show whether futures markets do indeed tend to lead the cash market. A number of studies have examined the temporal relationship between the futures and cash index returns. Kawaller et al (1990) examine whether the intraday S&P500 index futures and S&P500 index price volatility has changed notably in recent years, and whether intraday volatility in futures prices has systematically led to intraday volatility in the index. They address these issues by calculating variance measures for minute-to-minute futures and index price changes on a daily basis and across 30-minute intervals for the fourth quarters of 1984, 1985, and 1986. These measures indicate that average intraday volatility for both S&P500 futures and index prices increased from 1984 through to 1986. Kawaller et al (1990) found that the S&P500 futures lead the S&P500 index returns by 20 to 45 minutes, while the lead from cash to futures rarely last one minute.

Stoll and Whaley (1990) used data that are obtained from three separate sources; the Chicago Mercantile Exchange (CME), the Chicago Board of Trade (CBOT), and Francis Emory Fitch, Inc.

---

[5]See section 2.1 of chapter 2.

The CME provided the S&P500 index and index futures price data for the period April 1982 through March 1987. The CBOT provided the Major Market Index (MMI) and MMI futures price data for the period July 1984 through March 1987, with Fitch provide transaction-by-transaction data for IBM during all trading days for the period 1982 through 1986. Stoll and Whaley (1990) report that the S&P 500 and Major Market Index (MMI) futures tend to lead the stock index returns by about five minutes on average, but occasionally by as long as ten minutes or more. However, their results show some weak positive predictive effects of lagged stock index returns on current futures returns. After that, Chan (1992) examined two sample periods from August 1984 through to June 1985, and January through to September 1987, using the intraday lead-lag relationship between returns of the Major Market cash index and returns of the Major Market Index futures and S&P500 futures. Chan (1992) finds that the futures leads the cash index and weaker evidence that the cash index leads the futures in the MMI futures and the S&P500 futures markets. He also finds that the lead-lag relationship is largely robust to varying market conditions.

Abhyankar (1995) used a data set consisting of hourly FTSE100 cash and index futures data from April 1986 through to March 1990. Abhyankar (1995) divides the entire sample period into three natural sub-periods. The first period is from April 1986 to October 1986, and is the period prior to the introduction of the major structural reforms in the International Stock Exchange. The second period extends from October 1986 to September 1987. The third sub-period of analysis includes the time following the 1987 crash, January 1988 to March 1990. Abhyankar (1995) examines the returns and volatility dynamics of the FTSE-100 stock index and stock index futures markets. By using the hourly returns between 1986 and 1990, Abhyankar examines the lead/lag relationship between the two markets, during the three periods of pre-liberalisation, post-liberalisation and post-crash. Abhyankar (1995) concludes that a contemporaneous relationship exists in both volatility and returns between cash and futures markets, whilst for returns it also appears that futures lead the cash market. However, periods of extreme news upset this pattern in that no clear lead/lags exist, although there is a greater suggestion that futures lead. These results concur not only with prior beliefs but also with results elsewhere. The general conclusion is that the returns in the futures market seem to lead the cash market returns. There is, however, some weak evidence of predictive ability from cash to futures. Pizzi, Econommopoulos, and

O'Neil (1998) carried out an examination of the relationship between stock index cash and futures markets using a cointegration approach. They used price data on the S&P500 stock index, the three-month and six month S&P500 index futures contract, from the CME. The data are between January 1987 and March 1987. Both cash and futures index are tested for cointegration using the Engle-Granger two-step procedure. The analysis for both indices indicate market efficiency and the speed of adjustment coefficients indicates stability. Pizzi et al (1998) concluded that both the three- month and six-month futures market leads the cash market by at least 20 minutes. The cash market leads the three-month futures by at least three minutes and the six-month futures by at least four minutes. Therefore, the futures market does tend to have a stronger lead effect.

3.2 Hedging Effectiveness.

The modern analysis of the hedging effectiveness of stock index futures was started by Figlewski (1984). Since then, a considerable amount of research involving this topic has been undertaken. Again, hedging is traditionally viewed as a risk reduction strategy and the effectiveness of a hedge is usually judged by the ability of the futures position to reduce the variance inherent in the unhedged or cash position. The traditional hedge strategy involves hedgers taking a futures position which is equal in magnitude and opposite in sign to the established cash position. This traditional approach is taken to be risk minimisation, established by undertaking additional investment whose risk cancels out the initial risk. The hedge ratio in this traditional approach is unity. This means the cash and futures prices move closely together and if proportionate price changes in one market exactly match proportionate price changes in the other market, then price risk will be eliminated.

Previously, Johnson (1960) pointed out that researchers have concentrated on three hedge strategies involving constant hedge ratios: the traditional one-to-one hedge; the beta hedge; and the minimum variance hedge. With all three strategies it is necessary to calculate the hedge ratio. The minimum variance hedge ratio prescribes the number of futures contracts required for a unit of cash position to minimise the risk. To determine the usefulness of the futures contract as a hedging vehicle, one relies upon the concept of hedging effectiveness, which is the proportional risk reduction generated by the risk minimising hedge strategy. The relevance of futures hedging should be evaluated on the basis of its effect rather than on the magnitude of the hedge ratio. This effect is called the hedging effectiveness (Ederington, 1979). The usual economic rationale for futures is that they facilitate hedging. In other words, these instruments enable investors who hold the underlying assets to transfer the risk of price change to individuals who are more willing to bear such risk.

Hedging has been extensively studied by various researchers, in different situations. Traditional measures of hedging effectiveness focus on risk reduction. Lindahl (1989) used the traditional measure of hedging effectiveness on futures price changes compared to cash price changes. One example compares a hedge of Alaska North Slope (ANS) crude oil with a hedge of West Texas Intermediate (WTI) crude oil, which is listed crude oil futures contract traded on the New York Mercantile Exchange and represents the futures position for both hedges. The hedges are compared using daily closing price data collected from the Wall Street Journal for the period January 1987 through May 1988. The nearest futures contract is used and the futures price data is identical for both hedges. Another example compares a hedge of the S&P500 cash index with S&P500 futures for two weeks proceeding the October 1987 market crash against the two weeks during and after the crash. Stock index futures prices were widely publicised as selling at unusual discounts to cash prices during and immediately after the crash, so more basis risk and a lower R^2 is expected for the second half of the month. Daily closing prices for the S&P500 Index and the nearest futures contract on the S&P500 Index were collected from the Wall Street Journal for the month of October 1987. Lindahl found when comparing hedges with different futures data but the same cash data, higher R^2s are consistent with lower hedging risk and greater hedging effectiveness, and when comparing hedges with different cash data, however, higher R^2 s are always consistent with lower hedging risk. Thus, studies can not rely on R^2 to make relative hedging effectiveness judgements for different cash positions or different cash-futures data sets. For the two examples, R^2s on price levels were also compared and higher price level R^2s were consistent with lower hedging risk.

3.3 Stock Index Futures Markets.

Since the launch of stock index futures in the USA in 1982, there has been rapid growth in the volume and value of trading in index futures, with several studies had been carried out concerning stock markets. For example, Junkus and Lee (1985) obtained cash and closing prices for three index futures from the Wall Street Journal during the period, May 1982 through to March 1983. The three index futures were Kansas City Exchange, New York Exchange, and Chicago Exchange, for each month on each exchange three different contract maturity were used to calculate the ratio estimates: they are a short maturity, a long maturity, and an intermediate maturity contract. Junkus and Lee (1985) set out to test the applicability of traditional commodity futures hedging models to the new stock index futures contracts. They examined four particular models of hedging behaviour applied to stock index futures which capture a wide spectrum of attitudes about risk and return. These models are the following: the traditional one-to-one hedge; a variance-minimizing model first formulated by Johnson (1960). This model is associated with the low-risk portion of the risk-return spectrum; utility maximization model devised by Rutledge (1972), in which mean return is maximised subjected to a constraint on variance of return; and finally the basis arbitrage model first suggested by Working (1953), where the hedger attempts to use relative movements in the cash and futures markets to improve return while retaining the risk-minimising framework of the traditional hedge.

Junkus and Lee (1985) found that the optimal hedging positions in stock index futures were markedly different from the consistent one-to-one short hedge, and in some cases called for hedging behaviour considered speculative, with either long positions in both the futures and the index portfolio or a short position in futures greater than the value of the underlying index portfolio. They also found that the optimal hedge was less than one, the hedger using the traditional strategy would have a tendency to over hedge under the variance minimising model and the utility maximisation model, overpaying on transaction and margin costs. Moreover, Junkus and Lee (1985) also found that when comparing the traditional hedge to the basis arbitrage model, the hedger could improve his profit by using the basis arbitrage hedge, but might sacrifice variance reduction to do so.

Using the traditional hedge could at times result in a larger reduction of variance compared to an unhedged portfolio. The futures markets may give hedgers the opportunity to minimize risk through hedging their cash position. The traditional hedge may not minimise risk because the cash and the futures markets may not move perfectly together, to take account of this lack of perfect correlation and identifies the hedge ratio which minimises risk. The minimum variance hedge strategy may be used as it does not require the cash and future prices to have a one-to-one relationship. Moreover, if the hedge ratio is time-varying the multivariate GARCH model may be employed to estimate the time-varying hedge ratio. Hedge ratios calculated from the GARCH model may lead to a lower conditional variance of market returns than those based on the traditional method.

Park and Switzer (1995) estimated the risk-minimising futures hedge ratios for three types of stock index futures: S&P500 index futures, Major Market Index(MMI) futures, and Toronto 35 index futures. They estimated the optimal hedge ratio by modelling the distribution of stock index and futures price changes using the GARCH model. Park and Switzer (1995) used cash and futures markets data. The cash market data consists of daily closing prices for S&P500 index, MMI, and Toronto 35 index. The futures data correspond to daily settlement price for the three futures contracts. The data period is June 1988 to December 1991. Based on the substantial evidence of time-varying distribution, it is only natural to consider a time-varying distribution to estimate the optimal hedge ratios for index futures. Park and Switzer (1995) used the bivariate GARCH model to capture the time varying distributions of cash and futures price changes for three types of stock indexes. The GARCH based hedge ratios show considerable variations across the data period. This may indicates the unreliability of the constant hedge ratio based on the conventional risk-minimising estimation methods. Therefore, Park and Switzer (1995) indicated that the hedging strategy using the GARCH method is potentially superior to other conventional methods including the constant hedge with cointegration (OLS-CI).

Moreover, Park and Switzer (1995) compared hedging effectiveness of four types of hedging models. First, the naive hedging model, which is the simplest way to hedge risk. Second, is the OLS hedge, third is the OLS with cointegration between cash and futures (OLS-CI). The final model is the bivariate GARCH model. The OLS-CI model shows a better fit than the OLS model.

However, the GARCH model describes the distribution of cash and futures price changes better than both of the constant hedge ratio models. Most of the parameters are significant in explaining the time-varying distribution of cash and futures. The high significance of the constant correlation between cash and futures price changes is constant over time. Compared to OLS and OLS-CI hedge ratios, the GARCH hedge ratios show considerable variation over time for all three types of index futures. This variation occurs even though the stock markets were not particularly volatile over the period. The result is expected given the significance of the GARCH model parameters. The variances and covariances in the GARCH model are constantly changing through time and the constant hedge ratios are clearly unable to recognise the trend in the cash and futures price changes. Park and Switzer (1995) noted that the GARCH hedge ratio changes over the sample period. These changes takes longer for the GARCH hedge ratio to stabilise after each jump. The percentage variance reduction of GARCH hedge over the three alternative hedges shows improvement of hedging effectiveness through GARCH over the conventional methods. The hedge performance of different hedging methods is more reliable to measure hedge effectiveness for the out-sample period. Park and Switzer compared the performances for each type of hedge by computing hedge ratios each week and calculated the variance of the returns over the sample. They also found that all four types of hedging reduced the variance of the cash portfolio significantly.

More recently, Choudhry (1999) carried out a study on the time-varying distribution and hedging effectiveness of three Pacific-Basin stock futures using daily stock returns from the cash and futures markets. The three markets studied by Choudhry (1999) are Australia, Hong Kong, and Japan. The data period used for these markets start from January 1990 to December 1998. For each country two indices of futures prices based on two different expiration dates of the futures contract are used. The effectiveness of different hedge ratios depending on different estimation procedures are investigated. The hedging effectiveness is compared by checking the variance of the portfolio created using the hedge ratio. The lower the variance of the portfolio the higher is the hedging effectiveness of the hedge ratios. The methods of the traditional hedge, and the minimum variance hedge ratios are constant hedge ratios while the bivariate GARCH hedge ratio is time-varying. The optimal hedge ratios are estimated by OLS regression (constant) and the GARCH model.

Choudhry (1999) found that in all cases the constant hedge ratios are positive and significant. Choudhry shows considerable variation in the movement of the time-varying hedge ratios around the constant hedge ratios. He mentioned that a surprising feature of the results is that the constant hedge ratios and the time-varying GARCH ratio all provide quite similar hedging performance. However, there is evidence presented which indicates that the hedging strategy using the bivariate GARCH method is potentially superior to the constant hedge ratios. Reducing the length and time of the out-of-sample period does improve the performance of the time-varying hedge ratio. Choudhry (1999) pointed out that the inconsistent results may be due to the complexity of the GARCH model.

This section relies heavily on the Lindahl (1992) paper which refers to the Beta (β) hedge as the portfolio's beta. The traditional one-to-one hedge ratio calls for a futures position that is equal in magnitude but opposite in sign to the cash position. The Beta hedge ratio (β) is used when the traditional hedge is considered to be inappropriate in some circumstances. The beta hedge strategy is very similar to the traditional hedge strategy, but it takes account of the fact that the cash portfolio to be hedged may not match the portfolio on which the futures contract is written. This might be interpreted as matching the cash and futures positions. However, when the cash position is a stock portfolio, the number of futures contracts for full hedge coverage needs to be adjusted by the portfolio's beta (β). As stated in chapter two Beta (β) is the coefficient of the independent variable in a regression of market returns (the independent variable) on cash portfolio returns (the dependent variable). It is equal to the covariance between the portfolio's return and the market's return divided by the variance of the market's return.

A beta (β) of one refers to a portfolio of average volatility. For example, Lindahl reported that beta (β) of 1.18 means the portfolio's return will rise or fall 1.18 times as fast as the average market return, and 1.18 then becomes the appropriate hedge ratio. Thus, Portfolios with $\beta > 1$ call for larger futures positions, and portfolios with $\beta < 1$ can be fully hedged with smaller futures positions. Lindahl (1992) examine the stability of the hedge ratio for the Major Market Index (MMI) and S&P 500 stock index futures contracts with respect to hedge duration and time to contract expiration. This study uses MMI data from 1985 to1989 and uses S&P500 data from 1983 to1989. Cash and futures data on the MMI are from the Chicago Board of Trade through to 1988. MMI data from 1989 is collected from The Wall Street Journal. Futures data on the S&P500 index are from the Chicago Mercantile Exchange for 1983-1989, while cash S&P500 data and 1989 futures data are from The Wall Street Journal. Hedge durations of one, two, and four weeks are compared, and these groups are further broken down by the number of weeks remaining until contract expiration. The hedge ratios are analysed to see if they exhibit predictable trends, and statistical comparisons are made with the Beta (β) hedge ratio. The results of this study show that the minimum variance hedge ratios for MMI and S&P 500 stock index futures contracts increase significantly as hedge duration increases from one to four weeks. However, the duration effect is influenced by the fact that longer hedge duration are lifted closer to contract expiration. When the sample is subdivided by weeks to expiration, minimum variance hedge ratios are found to approach the beta hedge ratio at contract expiration and the expiration effect is further analysed by estimating rates of convergence toward beta hedge ratio. Lindahl (1992) found that on average the minimum variance hedge ratios for one and two weeks MMI and S&P 500 hedge increase by about 1% per week during the last ten weeks of contract life. Lindahl states that when hedging an established cash position, hedging with futures should be viewed as a dynamic process.

Earlier, Figlewski (1984) looked at the effectiveness of the S&P 500 futures contract in hedging the risk associated with portfolios underlying five major stock indexes. He investigated the period from June 1982 to September 1983. These five major stock indexes represented diversified portfolios, two include large companies, two include small companies and one was much less diversified than the others. Figlewski included dividend payments which he found did not alter the result regarding the hedging effectiveness. He found that hedge performance using the minimum variance hedge ratio is better than using the beta hedge in all cases. Figlewski (1984) states that for the larger capitalisation stock, risk was reduced by more than 70% when the minimum variance hedge ratio was used, and hedging effectiveness was reduced for smaller stocks. Also, hedging performance was found to be inferior for overnight hedges compared to one week and four weeks hedges.

Figlewski (1985) followed up his previous work by examining the performance of stock index contracts in hedging risk in various stock portfolio over holding periods of one day to three weeks. The actual performance of the three futures contracts in hedging several different stock portfolios during the period June 1982 to December 1982 is investigated. The three futures contracts utilized were the index futures contract which was introduced by Kansas City Board of Trade on the February 1982, the S&P 500 index futures which was introduced in April 1982 by the CME and the New York Futures Exchange's contract on the NYSE Composite Index. All of the contracts are of similar design and its behaviour is meant to reflect the movement of the whole stock market. Figlewski (1985) analysed the ability of the new stock index futures contracts to hedge risk in a stock portfolio for a short period of time (three weeks hedge). He showed that hedging a stock portfolio with index futures will involve substantial basis risk arising from three sources. First, fluctuations in the value of a given stock portfolio are only imperfectly correlated with changes in a market index. Second, when the hedge is not held until the futures contracts expires, additional risk arises due to changes in the price difference between the futures contract and its underlying index over time. Finally, the futures contract can only hedge against the risk of stock price movement, and risk arising from uncertain dividend payouts will remain. All three factors will play a role in determining hedging effectiveness and optimal hedge ratios.

Figlewski (1985) pointed out in general the hedge ratio which minimised the total risk for a hedged portfolio was below its beta. This minimum risk hedge ratio tended to increase, and the unhedgeable risk to decrease, with longer hedge duration. He also found that hedging was more effective for portfolios of large stocks than small stock portfolios. Figlewski (1985) restricted his analysis to hedge with a constant hedge ratio, while focussing on reducing portfolio risk with futures hedges and taking into account what happens to portfolios expected return in the process.

Butterworth and Holmes (1997) examined the hedging performance using both the FTSE-100 and FTSE-Mid250 stock index futures contracts over the period February 1994 to July 1995. They used 36 cash portfolios which comprised four indices and 32 investment trusts to evaluate the hedging effectiveness. This study demonstrated that in spite of the low volume of trading in the contract, the FTSE-Mid250 futures provides an important additional hedging instrument. The findings in relation to hedging broad market indexes show the superiority of the new contract over the FTSE-100 contract in relation to cash portfolios which mirror the FTSE-Mid250 indexes. In all cases, the average mean return is higher and the average standard deviation of returns lower when the FTSE-Mid250 contract is used as compared to the use of the FTSE-100 contract. The results also show that previous studies of hedging effectiveness have exaggerated the degree of risk reduction which can be achieved. Butterworth and Holmes (1997) show that in many portfolios, risk reduction of less than 20% is achieved. Thus, while the new contract does significantly add to the ability to hedge the risk associated with stock portfolios, for many portfolios there is still no satisfactory means by which to achieve substantial risk reduction. Butterworth and Holmes (1997) started by considering the impact of the length of the hedge by examining hedges one, two and four weeks duration, whether there existed expiration effects, and also of the performance of alternative methods for estimating the minimum average hedge ratio. They reported that the traditional hedge and the beta hedge are identical when the portfolio to be hedged is that which underlies the contract. The pattern of results for the traditional and beta hedge strategies for weekly hedge durations are reported to be very similar. When the cash portfolio to be hedged is that which underlies the contract, both contracts achieve very substantial reductions in risk (approximately 70%) in line with previous studies for the FTSE-100. As expected, hedging effectiveness is therefore improved when the duration of the hedge is increased.

Institutional investors today hold sizeable positions in stock. The stock index futures markets offer a number of attractive possibilities of risk improving, risk management and for enhancing return in equity investment. Hedging with futures also involves features which are unique to the stock markets. It emphasises that the effective risk of a stock depends on what other stocks are held. As different stock are combined in an investment portfolio some risk that associated with specific events to a certain firm or industry tend to be diversified away. Therefore, there is little disagreement in the literature that hedging can be an effective risk management tool for firms. However, when placing a hedge the hedger must determine the futures position to take to offset the price risk on his current or anticipated cash position. When direct hedges are placed the hedged quantity to cash quantity hedge ratio, is often assumed to be one. However, in instances involving cross hedging (hedging a cash commodity in a different but related futures market) the hedge ratio may deviate significantly from one because the prices of the two commodities may not perfectly correlated (one-to-one). Therefore, the hedge ratio should be empirically estimated. Disagreement, however, arises on the best procedure to estimate minimum risk hedge ratio. Some of the methods used show the hedge ratio is indeed related to the underlying objective function of the hedger, the nature of the relationship between the cash and futures prices, and whether the hedge is a storage hedge or an anticipatory hedge. These issues dictate the most appropriate technique to use to estimate the hedge ratio.

3.4 Commodity Futures markets.

Several researchers has focussed on investigating the distribution of commodity price change, as many commodity price changes appear to be time-varying. Consequently, price change began to be described with non-normal distributions. For example, Baillie and Myers (1991) compare the GARCH hedge ratios relative to the traditional methods. where the recognised that the knowledge of distribution of commodity cash and futures prices is crucial in constructing optimal hedging and trading strategies on commodity markets. Baillie and Myers (1991) used daily data of cash and futures prices for beef, coffee, corn, cotton, gold, and soybeans, which obtained from the Columbia Centre for the Study of Futures Markets data tape. The Futures data reflect settlement prices at the close of each day's trading. The proportionate reduction in the variance of the conditional return can be calculated for the GARCH and traditional estimates of the optimal hedge ratios, relative to unhedged policy. This comparison is based on the variance reduction, given that the GARCH model is the true data-generating process. Using GARCH hedge ratios reduces the conditional return variance below the traditional hedge ratios, but the gain from using the GARCH ratios is insignificant. The benefits of GARCH modelling might examine the reduction in portfolio variance between hedged and unhedged position, given that the GARCH model was the true data-generating process, against the alternative model with the traditional hedge, in which the covariance matrix was constant over time. Making this comparison, the proportionate reduction in the hedge portfolio is somewhat larger now in the GARCH model. On this basis, the GARCH modelling strategy outperforms the traditional regression method for estimating the optimal hedge.

Myers (1991) applied time-varying methods to a sample of wheat storage hedging and results are compared with no hedge and constant hedge outcomes using both in-sample, out-of-sample and combined sample performance evaluations. Myers (1991) outlines and compares two approaches for estimating time-varying optimal hedge ratios on futures markets. Both methods take account of relevant conditioning information but they differ in their degree of sophistication and ease of estimation. The first method involves calculating moving sample variances and covariances of past prediction error for cash and futures prices. This method imposes questionable restrictions on the time pattern of commodity price volatility. The second method is the generalized autoregressive conditional hetroscedastic (GARCH) model. This model provides a flexible and consistent framework for estimating time-varying optimal hedge ratios. It is found that time-varying optimal hedge ratio estimates computed from the GARCH model perform better than the constant estimates obtained using conventional regression technique.

Castelino (1992) tested several cash and futures market such as wheat and corn futures for the period January 1983 through to December 1985, and for T-bills and Eurodollar contracts the time period extends from January 1986 through to December 1989. Cash prices for wheat and corn are from the United States Department of Agriculture (USDA). Both prices represent bids for delivery and are traded at the Chicago Board of Trade (CBT). Cash and futures prices for the T-bill and are Eurodollar contracts are from Data Resources Incorporated (DRI). Using these data Castelino (1992) related the hedging strategies of the arbitrage hedger (hedging for profit) and the minimum-variance hedger (hedging to reduce risk). He showed that in unbiased futures markets, hedgers should be driven to hedge by expected profit. If the decision to hedge is made based on the expected profit, the hedger may consider whether it is worthwhile placing a minimum-variance hedge. The reason for this is that a minimum-variance hedge has no effect on expected profit, it only serves to reduce risk. The risk reduction afforded by minimum-variance hedging is put in perspective by comparing it to the risk of a full hedge (basis risk). If minimum-variance hedging can reduce risk substantially below basis risk, then it ought to be considered; otherwise it should not. In principle, a minimum-variance hedge ratio possesses a 'time dimension' i.e. the minimum-variance hedge ratio is low for hedges lifted far from contract expiration as the hedge-lifting date approaches contract expiration. Castelino (1992) concluded that if current futures prices are unbiased estimates of futures prices in the future, then the expected return on the hedge is unaffected by the hedge ratio. The hedge ratio, however, affected the risk of the hedge. A minimum-variance hedge ratio does exist. It is the hedge ratio that minimizes risk for the level of return implied by the basis. Castelino also concluded that the existence of a minimum-variance hedge ratio by no means implies that a hedger should use it at all times. The return implied by the basis at the time of hedge initiation should be a major factor in the decision to hedge or not to hedge. If the return is attractive, the hedger may choose to hedge using the minimum-variance hedge ratio otherwise the hedger should not. This is consistent with the theory proposed by Working (1953) that hedging takes place on the anticipation of a favourable change in the basis.

Witt, Schroeder, and Hayenga (1987) carried out a comparison of analytical approaches for estimating hedge ratio for agricultural commodities. They used data from the period between 1975 to 1984, for the Thursday closing prices of Minneapolis barley and Kansas City sorghum provided by the U.S. Department of Agriculture, Agriculture Marketing Service. Corn futures prices used were based on Thursday closing prices at the Chicago Board of Trade. Witt, Schroeder, and Hayenga (1987) examined optimal hedge ratios through price level regression, price change regression, and percentage price regression. To illustrate the differences among these alterative hedge ratio estimation approaches, each was estimated by using the same data to estimate cross-hedging relationships between barley and sorghum cash prices and nearby futures prices. They found none of the techniques to be statistically superior to the others, and instead they concluded that from practical point of view, the appropriate hedge ratio estimation model should depend on the hedger's objective function.

Myers and Thompson (1989) estimated the optimal hedge ratio for corn, soybean, and wheat storage in Michigan. The data were obtained from various issues of the CBOT Statistical Annual. The estimation period runs from July 1977 to July 1985; these data are weekly observations taken at the midweek closing price on the relevant market. In this study the hedger is assumed to be an agent that stores the commodity at harvest and intends to sell at the most advantageous time period to the next harvest. To hedge, the agent sells futures in a contract maturing just before the next harvest (July for corn and soybeans and May for wheat). The hedger then liquidates portions of the cash and futures positions at whatever time prior to the next harvest is deemed appropriate. Three conventional simple regression approaches to optimal hedge ratio estimation were applied. The correct approach to optimal hedge ratio estimation depends on the model that determines equilibrium cash and futures price movements. The usual simple regression approaches using price levels, price changes, and returns implicitly assume particular forms for the model. Myers and Thompson (1989) argued that the hedge ratio estimates traditionally used in the literature are inappropriate except under special circumstances. This is true because the traditional literature calculates the slope coefficient as the hedge ratio of the unconditional covariance between cash and futures prices to the unconditional variance of futures prices. Myers and Thompson (1989) suggested that a conditional information model takes into account the information which is available at the time the hedge is placed. However, Viswanath (1993) modified the Myers and Thompson (1989) model where changes in cash prices are regressed on changes in futures prices and the basis at the time the hedge is placed. Viswanath (1993) used daily data on wheat, corn, soybean prices in cents per bushel for the period January 1978 to December 1988 from the USDA. He estimated the hedge ratios under the traditional method and the basis-corrected method. The basis corrected methodology produces significantly smaller hedged portfolio return variances in many cases. He found that the improvement is not similar across the board, as there seemed to be no effect on corn hedges at all. However, for wheat and soybean hedges, a weak pattern is detected.

Bell and Krasker (1986) show that if the expected futures price change depends on the information set, then the traditional regression method will yield a biassed estimate of the hedge ratio. They also showed that this procedure will yield the correct results provided the hedge ratio itself is independent of the information set. More recently, Lence (1995) shows theoretically that hedge ratio estimates from regression models are sub-optimal in general, unless futures are unbiased and prices are specified in levels or in level changes. Lence's findings rule out regressions in price logarithms or in price ratios to obtain hedge estimates consistent with expected utility maximization. Krehbiel and Adkins (1993) studied metals markets in silver, copper, gold, and platinum. Prices of silver, copper, and gold futures contracts traded at the Commodity Exchange Inc, and platinum futures traded at the New York Mercantile Exchange. The data period used for silver was from May 1964 through May 1992; the sample for copper from January 1960 to May 1992; the sample for gold from June 1975 to June 1992; and the sample for platinum from January 1968 to April 1992. Krehbiel and Adkins (1993) examine the equilibrium relationships from these markets using the cointegration methodology. They found that tests for stationarity of the residuals from the cointegrating regression and tests based on the rank of the coefficient matrix from the maximum likelihood estimation of the vector autoregression indicate that futures contract prices and cash prices are cointegrated in the silver, copper, gold, and platinum markets. The Johansen maximum likelihood estimation procedure is used to test the parameter restrictions implied by the unbiased expectations hypothesis. Krehbiel and Adkins (1993) found that test outcomes for hypotheses in the platinum market provided evidence most consistent with the implied parameter restrictions. The hypothesis of unbiased expectations is rejected for the gold and silver markets. The cointegration tests indicate that the copper market is one in which economically meaningful departures from the no-risk premium exist. The estimated value of β is significantly less than one (β is the hedge ratio) indicating the futures prices is less than the expected cash price. However, the estimated value of α is significantly greater than zero (α is coefficient) which by itself is consistent with contango.[6]

Schwarz and Szakmary (1994) carried out cointegration tests using Engle and Granger's two step method between the cash and futures markets of three energy products (crude oil, heating oil, and unleaded gasoline). The data period used for the analysis extends from January 1984, to May 1991 for the crude oil and heating oil, with unleaded gasoline beginning in January 1985. The daily cash price data for par deliverable grade of West Texas International crude and New York unleaded gasoline is obtained from Platt's Oilgram Price Report. Cash price data for heating oil is from Tick Data, Inc. Daily closing futures prices for crude oil, heating oil and unleaded gasoline are obtained from Tick Data, Inc. Schwarz and Szakmary (1994) found futures prices are strongly cointegrated with their deliverable spot price. In particular, the residuals from the cointegrating regressions are highly stationary, and the cash and futures markets for each product are subject to the same non-stationary properties. As a result, the futures market is likely to serve as a viable hedge for the cash commodity. They also found that the cointegrating parameter in each case is significantly less than one, indicating that the futures price is less volatile than the cash for all three energy markets. The temporal properties of the three energy products and their futures markets are also examined and are found to be non-stationary with unit roots. It is argued that the presence of a unit root is often a theoretical implication of models which postulate the rational use of available information by economic agents. The basic random-walk model, which is a special case of a unit root, does as well or better than many structural and complex time-series

[6]See section 2.1 of chapter 2.

models in forecasting economic variables. Unit root tests on the GARCH based hedge ratios often suggest that they are stationary. This might suggest that hedging activities based on the GARCH model would have been easy to implement.

Meanwhile, Crowder and Hamed (1993) used cointegration to test the efficiency of the oil futures market, using monthly data from the New York Mercantile Exchange (NYMEX) for the period from March 1983 to September 1990. The futures price is defined as the closing price of a futures contract 30 days prior to the last day of trading on the last trading day of the corresponding futures contract. They analysed the cointegration properties of the oil market to allow valid inference on market efficiency. They argued that the simple efficiency hypothesis implies that the expected return to futures speculation in the oil futures markets implies that the expected return to speculation in the futures market should equal the risk-free rate of return.

3.5 Volatility Estimation and Time-Varying Hedge Ratios.

Again, since the introduction of stock index futures markets in the early 1980s, several studies have investigated while restricting the hedge ratio to be constant over time. However, if the joint distribution of stock index and futures prices is changing through time, estimating a constant hedge ratio may not be appropriate. Estimating optimal or minimum risk hedges with futures contracts should use the time-dependent conditional variance models such as the Generalized Autoregressive Conditional Heteroscedastic (GARCH) and the Autoregressive Conditional Heteroscedastic (ARCH) model of Engle (1982) and their extensions. The success of the ARCH and GARCH models, despite their relatively short life, lies in the fact that ARCH and GARCH models are able to capture the volatility clustering and unconditional non-normality in financial data, and their similarity with standard time-series techniques used to estimate the conditional mean, i.e ARMA models. The GARCH structure is similar to that of an ARMA. GARCH models postulating an ARMA structure in the squared error term.

The potential sources of the time-varying volatility in financial markets including the 'noise' approach, and the theoretical model of Timmermam (1995), where the source of volatility clustering is incomplete learning and limited knowledge of the process generating fundamentals. Given a stochastic dividend process, individuals are unable to ascertain the exact value of the growth rate and thus form an estimate using current and lagged dividends. Additionally given the dependence of the present value stock price upon this estimate, small dividend shocks can have a disproportional effect upon stock prices as agents may revise their estimates. Where an economic agent's is estimates persistently deviate from the true growth rate, this learning effect can account for volatility clustering in stock returns. However, by far the most dominant rationale for time-varying conditional volatility in financial markets in the information flow hypothesis (Clark, 1973) and variants thereof. Clark argued that stochastic prices could be modelled as a subordinate stochastic process with stock prices evolving at different rates during identical intervals of time according to the flow of information, with prices evolving faster when unexpected information flows into the market. Clark claimed that the distribution of prices changes is a mixture of normals with changing variance, the daily price change being the sum of a random number of within-day price changes. Thus, daily price changes follow a mixture of normals, whereby the observed daily price changes will follow a non-normal distribution, given that the directing process is unobservable value used as a proxy, thus generating the observed positive correlation between the variance of price change and volume. Thus, variance and volume are positively correlated, with volume influencing volatility, again motivating the GARCH process as resulting from the time dependence in the rate of information arrival. Time-varying volatility can be introduced through the GARCH model of Engle (1982) and Bollerslev (1986). Engle (1982) introduced ARCH[7] models, which were generalised by Bollerslev (1986), and are proving to be particularly useful in the modelling of time variability of hedge ratios. The GARCH model represents a flexible specification for modelling time-varying volatility in asset prices. Thus, the GARCH model has significant theoretical advantages over moving sample variance and covariances to estimate.

A natural question is whether the additional effort required to estimate the GARCH model provides a significantly improved hedging performance compared to simpler approaches? Myers (1991) investigated this question by estimating the wheat futures optimal hedge ratios by means of the time-varying methods. Myers focussed on the May and December contracts at CBOT.

[7]See section 4.4 of chapter 4.

Consider an investor that takes a long position in wheat, where the investor buys and stores wheat for later resale at a price which is unknown at the time of purchase. The investor can hedge the long cash position by selling futures. In the example, it is assumed that the investor takes out futures positions in one of these contracts and re-evaluates his/her portfolio on weekly basis. Each week the portfolio may be adjusted to reflect changing information and economic conditions. When a contract matures, futures positions are rolled over into the same contract month of the next year, because portfolio adjustment is assumed to occur on a weekly basis as weekly data are used in the empirical research. The sample period in this example runs from June 1977 to May 1983, and the data are the mid week closing price. This data are split into two parts, the first for estimation and within-sample performance evaluation and the second for out-of-sample testing.

However, Myers (1991) applied two time-varying methods on wheat storage, to compare and estimate time-varying optimal hedge ratios on futures markets. The first method involves calculating the moving sample variance and covariance of past prediction errors for cash and futures price. This method is easy to apply but is also ad hoc and imposes questions on the time pattern of commodity price volatility. The second method is the GARCH model. As studied above this model provides a flexible and consistent framework for estimating time-varying optimal hedge ratio. The results of these two methods are compared with no hedge and constant hedge outcome using both within-sample and out-of-sample performance evaluations.

The optimal hedge ratio computed from GARCH model performs marginally better than constant estimates obtained using the conventional regression technique. Myers (1991) also mentioned that the extra expenses and complexity of GARCH model do not appear to be warranted. Separate bivariante GARCH models are estimated for cash and May futures prices, and for cash and December futures prices. The preliminary results are consistent with the findings of a number of other studies on the conditional distribution of asset prices (Engle and Bollerslev, 1986). Again Myers (1991) noted that estimated hedge ratios from the time-varying method have a tendency to move together, and they both fluctuate considerably over time. However, fluctuations in the moving sample variance and covariances hedge ratio are clearly more pronounced than in the GARCH hedge ratio. This suggests that futures positions would have to be adjusted by much greater amounts when using the moving sample variances and covariances and models compared to the GARCH model.

Optimal hedge ratio estimates from the constant conditional covariance matrix and moving sample variances and covariances models are computed using standard techniques. For the GARCH model, in-sample hedge ratio are constructed using the parameter estimates along with realised values of cash and futures prices available up to the portfolio being adjusted. These sample estimates are therefore based only on information that is available at the time each hedging decision is made. Myers (1991) pointed out that more efficient use of available information can be very costly by updating the GARCH model's parameter estimates as each new observation becomes available.

Moschini and Myers (2002) developed a multivariate GARCH parameterization suitable for testing the hypothesis that the optimal futures hedge ratio is constant over time as a special case, while allowing for a flexible time-varying distribution of cash and futures prices. If the joint distribution of cash and futures prices is time-varying, then the optimal hedge ratio may also be time-varying. However, the optimal hedge ratio can still be constant even if $Var(f_t /\Omega_{t-1})$ and $Cov(p_t,f_t /\Omega_{t-1})$ are time-varying, as long as the covariance term is proportional to the variance term i.e. $Cov(p_t,f_t /\Omega_{t-1}) = \gamma_0 Var(f_t /\Omega_{t-1})$, for all t for some constant γ_0. The approach overcomes the limitation that the null hypothesis of a constant hedge ratio was identified jointly with other restrictive conditions. The new parameterization is particularly useful for estimating time-varying optimal hedge ratios and testing the null hypothesis that they are constant over time.

They applied cash and futures prices corn based on weekly data for the time period between 1976 to 1997 for their estimation of the optimal hedge ratio. Significant GARCH effects are present even when accounting separately for the significant seasonality and time to maturity. They conclude by rejecting the null hypothesis that the optimal hedge ratio is constant at any significance level. They also reject the null hypothesis that optimal hedge ratios vary only systematically with seasonality and time to maturity effects at essentially any significance level. The optimal hedge ratio is time-varying in ways not explained by these elements.

3.6 Conclusion and Research Motivation.

Opinions are divided between researchers when dealing with hedging. This disagreement is traceable to imperfect concepts that emerged in connection with early academic studies of futures trading. Futures contracts play a leading role by creating more opportunities for investors through the introduction of negative correlation not typically found in the cash markets. In the case of commodity and stock index futures, futures contracts provide investors with the opportunity to avoid market risk which is often difficult to be avoided using cash assets. Several studies have investigated the optimal hedge ratios for commodity and stock index futures markets. Estimations of constant and time-varying models were used for different data samples and time periods. Evidence of the effectiveness of time-varying hedge ratios is mixed in the literature. Results on the optimal hedge ratio reported in the literature indicate the unreliability of the constant hedge ratio based on the conventional risk minimising estimation methods. The traditional hedge ratio estimation approach relies upon regression coefficients established from historical prices. Prior evidence indicates a close link between cash and index futures markets, which may show evidence of cointegration between cash and futures prices. This may be significant to apply the error correction term to the time-varying (GARCH-X) model to create hedge ratios of superior effectiveness for the stock and commodity markets understudy. This method investigates and takes into consideration the impact of short run deviation on the hedge ratios which is different from other methods in the literature. The empirical results of commodity and stock index futures chapters seek to examine the hedging effectiveness for several methods and the impact of the error correction term on the time-varying hedge ratios for different time periods. The following chapter discusses the econometric techniques used to estimate the hedge ratios.

The motivation for this thesis is to empirically investigate the hedging effectiveness of stock and commodity futures markets using both conventional (constant) and time-varying hedge ratios. Existing evidence of the improvement offered by time-varying hedge ratios is mixed. Previous related research applies different hedging methods to estimate the hedge ratios. Myers (1991), Baillie and Myers (1991), Myers and Thompson (1989) and Choudhry (1999) applied a time-varying (GARCH) model to estimate the hedge ratio for different futures markets and then compared it to different conventional methods of reducing risk. The striking feature of previous research findings is that the time-varying method performs better in terms of the variance reduction in most cases but not all.

This thesis was inspired by Park and Switzer (1995) when they pointed out that in order to account for potential cointegration between cash and futures prices, the first moment can be modelled with a bivariate error correction model and in order to account for the time-varying variances and covariances, Park and Switzer (1995) suggested the second moment can be parameterized with a bivariate constant correlation GARCH (1, 1) model. In this thesis, an extended bivariate GARCH model with error correction term (GARCH-X) for the variance is applied as an alternative method to estimate the hedge ratios. One of the main aims of this thesis is to investigate whether this method may give an opportunity for investors to enhance risk transfer via futures markets. The main contribution of this thesis relative to other research studies is the application of the GARCH-X model to estimate the hedge ratios. In this method I used the error correction term in the conditional covariance equation to investigate how the short-run deviations from a long run relationship between cash and futures price impact on the hedge ratio, and subsequently test its effectiveness. The second main contribution is to provide evidence on the implementation of time-varying hedging in the presence of transaction costs, an aspect which has been neglected in the previous literature.

Engle and Yoo (1987) show that the short-run deviation from a long-run cointegration relationship has important predictive power for the conditional mean of a cointegrated series. Lee (1994) noted that if short-run deviations affect the conditional mean, they may also affect conditional variance, then conditional heteroscedasticity may be modelled as a function of lagged conditional error correction term. Taking this into consideration, Lee (1994) examined the behaviour of the variance over time as a function of short run deviation, whereby an increase in volatility is expected when shocks to the system impact on both the mean and variances.

The hedge ratio is defined by the covariance between cash and futures returns divided by the variance of futures return. An innovation in this thesis is to account for the fact that if the short-run deviation between cash and futures prices increases or decreases then the covariance between the cash and futures prices increases or decreases, respectively. In other words, if the deviation changes then covariance changes, hence the hedge ratio will change. In theory, the prior expectation was that modelling which took account of the short run deviation from the long run relationship would reduce risk more than the other methods. The evidence provides insights to investors seeking to hedge a position in commodity and stock markets.

The hedge ratio estimations are carried out using several hedging methods. The empirical comparison of hedge ratios is for stock and commodity futures markets and investigation of whether the short run deviation from the long run relationship between cash and futures prices has an effect on hedging. Both within-sample and out-of-sample testing is employed. One and two years out-of-sample time periods were applied. In order to investigate the out-of-sample hedging effectiveness of the methods involved, hedge ratios based on the bivariate GARCHX, bivariate GARCH and the minimum variance are calculated for the relevant two and one years out-of-sample time period for the stock and commodity futures markets. The aim is to offer a more reliable measure of hedging effectiveness, as the forecasts are conducted for each day for stock and commodity markets for the out-of-sample periods. The application of two out-of-sample time periods were conducted in order to identify whether changing the length of out-of-sample time period indicates changes in the results.

Daily data was used to hedge the risk in volatile markets, as the market may drop frequently from day-to-day indicating that using lower frequency data would leave investors exposed to risk. The differences of hedge ratios from day-to-day in the markets being studied should provide analysts and portfolio managers with evidence to make a judgement on whether the hedge ratio has changed by a significant amount in order to justify the transaction costs of futures markets trading. The evidence may motivate portfolio managers to increase/decrease the size of investment in the market by buying/selling futures. A fund manager may buy futures if he/she thinks the market is about to rise, where he/she may sell if the market is about to fall.

Trading volume in futures has expanded during the past twenty years. Futures markets provide very low transaction costs, it is far less expensive for a stock and commodity portfolio manager to reduce market exposure by selling the equivalent amount of stock and commodity futures contracts than by selling the underlying stocks or commodity. Therefore, an empirical investigation of time-varying hedging with transactions costs was conducted in the thesis to investigate the trade off between the risk reduction and transactions cost, and thus to determine the practicality of the time-varying hedging methods. This chapter was partly motivated by Park and Switzer (1995) where they suggested an alternative strategy which involves less frequent re-balancing of time-varying portfolios as a topic for future research. According to the trade off between risk reduction and transaction costs, portfolio managers may have to make frequent and sometimes substantial adjustment to their portfolio as the hedge ratio changes on a daily basis.

In anticipation of the results, the evidence indicates that the GARCH-X model is potentially efficient for hedging in some cases of the stock index futures markets, but this is not the case for the commodity futures markets. Therefore the advice to investors is not general across the markets involved and the performance of alternative hedging rules will have to be examined on a case-by-case basis, as the superior hedging performance varies from case to case. The next chapter presents the methodology for the thesis, while the subsequent three chapters present the findings.

CHAPTER FOUR

4.0 TIME SERIES AND ECONOMETRIC MODELLING.

This chapter discusses different methods to test for unit roots and cointegration. It also discusses the methods applied to estimate the hedge ratios for stock and commodity futures markets. The aim of this chapter is to discuss several methods of analysis in order to offer alternative means of evaluating the data regarding the presence of unit roots by providing direct evidence of stationarity and non-stationarity. This chapter also discuss cointegration methods and whether the time series data under study demonstrate a long run relationship between cash and futures prices. It would be useful to perform tests of null hypothesis of stationarity as well as tests of the null hypothesis of a unit root. This chapter provides methodologies to tests the null hypothesis of a unit root against the alternative of stationarity using the ADF method and also test of the null hypothesis of stationarity against the alternative of a unit root using the KPSS test. The KPSS test applied can handle heteroscedasticity, and it is also more robust to auto-correlation than the ADF test. Lee and Schmidt (1996) show that KPSS test is consistent against stationary long memory. Also Lee and Amsler (1997) showed that the KPSS statistic can distinguish consistently between short memory, stationary long memory and non-stationary long memory. Meanwhile, to test for cointegration relationships between cash and futures prices two methods were applied in the forms of Engle and Granger (1987) and Phillips and Hansen (1990) methods. The techniques are discussed prior to applying the conventional and time-varying hedging methods to estimate the hedge ratios. The estimation methods of the hedge ratios are to be discussed later in this chapter. This discussion also outlines the application of the cointegration results to the time-varying method of the Generalised Autoregressive Conditional Heteroscedasticity (GARCH-X) as the main contribution in the thesis.

4.1 STATIONARY AND NON-STATIONARY VARIABLES.

The concept of a stationary time series is crucial for analysing financial data. Any time series data can be thought of as being generated by a random process. A time series is defined as a sequence of numerical data which each item is associated with a particular instant in time (Maddala, 1992). This data may be collected in the form of quantitative or qualitative data. In this thesis, the time series applied is quantitative data in the form of daily stock index and commodity prices. The success of any econometric analysis ultimately depends on checking the stochastic structure of the data under study in order to avoid the problem of spurious regression[1]. To do that, we check on whether a variable is stationary or not. Time series data is regarded as a stationary if its mean value and its variance do not vary systematically over time. A non-stationary variable will not have a constant mean and its variance increases with the sample size. A non-stationary time series is set to contain unit roots. However, many non-stationary time series can be transformed to stationary time series by differencing them one or more times. This is called integrated non-stationary process. The number of times (d) that an integrated process must be differenced to be stationary is said to be the order of the integrated process. The number of times a variable needs to be differenced in order to induce stationarity depends on the number of unit roots it contains. Consider a simple data generating process, this relationship is a first-order autoregressive process:

$$y_t = \rho y_{t-1} + \varepsilon_t \qquad (4.1)$$

The above equation shows y_t as a function of y_{t-1} and a disturbance term, ε_t, which captures random errors drawn from a normal distribution with mean equal to zero and variance of σ^2. The value of ρ determines whether y_t is stationary or not. If $|\rho|<1$ then y_t will be stationary, however, if $|\rho|>1$ then y_t will be non-stationary and explosive, y_t is also non-stationary if $\rho =1$. However, if the variable is non-stationary then it will have a unit root, which can be seen by rearranging the equation (4.1) as:

$$(1-\rho L)y_t = \varepsilon_t$$

[1]This section relies on Harris (1995).

Where L is the lag operator such that $Ly_t = y_{t-1}$ and its root ($L = 1/\rho$). To consider stationarity, it is necessary to look at different types of trend that can be found in variables. The following equation has a non-zero intercept:

$$y_t = \beta + \rho y_{t-1} + \varepsilon_t \tag{4.2}$$

and if $\rho = 1$, then by rearranging the equation and accumulating y_t for different periods with an initial value of y_0, the stationary series y_t can be rewritten as:

$$y_t = y_0 + \beta t + \sum_{j=1}^{t} \varepsilon_j \tag{4.3}$$

Thus y_t does not return to a fixed deterministic trend ($y_0 + \beta t$) because of the accumulation of the random error terms[2]. However, when $\rho=1$, y_t will follow a stochastic trend, as it will drift upward or downwards depending on the sign of β. This can seen by taking the difference of y_t, giving $\Delta y_t = \beta + \varepsilon_t$, with the expected value of Δy_t being equal to β, the growth rate of y_t. Since the first difference of y_t is stationary, Δy_t fluctuates around its mean of β and has a finite variance. In contrast, consider the following data generating process (dgp):

$$x_t = \alpha + \beta t + \varepsilon_t \tag{4.4}$$

Where $\alpha + \beta t$ is a deterministic trend (stationary) and the disturbance, ε_t is stochastic trend (non-stationary) component. Since ε_t is stationary, x_t is said to be trend stationary, it may trend but deviations from the deterministic trend are stationary. Both equation (4.3) and (4.4) have the same form and both exhibit a linear trend, except that the disturbance term in (4.3) is non-stationary. Therefore, by considering the deterministic (stationary) and stochastic (non-stationary) trend, it has been possible to contrast difference-stationary and trend-stationary variables, where the presence of a stochastic trend as opposed to a deterministic trend can make testing for unit roots complicated.

---

[2]It should be noted that the linear trend, β_t, in the equation (4.3) mentioned reflects the accumulation of the successive β intercepts for different periods.

If a variable is stationary then current shocks of any variety will not have any long term effects on the series. In the following simple regression model:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{4.5}$$

There are four cases to consider when the model above may contain non-stationary variables. Firstly, both y_t and x_t could be stationary which would mean that the classical regression model is appropriate. Secondly, the series y_t and x_t could be integrated of different orders, which means that a regression equation using these variables would be meaningless. Thirdly, the series y_t and x_t could be integrated of the same order and the residual sequence contains a stochastic trend (non-stationary), meaning the regression would be spurious and the results meaningless. And finally, the non-stationary series y_t and x_t could be integrated of the same order and the residual sequence could be stationary. In this case the series are said to be cointegrated. Further discussion of cointegration appears in section 4.3. Prior to estimation of the hedge ratios using time-varying and conventional methods, it necessary to examine the stochastic structure of the data involved.

4.2 TESTING FOR UNIT ROOTS.

Unit root tests assess whether a time series is non-stationary and integrated of particular order. If a variable contains a unit root then it is non-stationary and unless it combines with other non-stationary series to form a stationary cointegration relationship, then regressions involving the series can falsely imply the existence of a meaningful economic relationship. As mentioned earlier, testing for the presence of unit roots is carried out to avoid the problem of spurious regression. The standard tests for unit roots are biased toward accepting the null hypothesis of non-stationary when the true d.g.p. is stationary but close to having a unit root when dealing with finite samples. It is important to test the order of integration of each variable in a model, to establish whether it is non-stationary and how many times the variable needs to be differenced to result in a stationary series. Testing for stationarity for a single variable is very similar to testing whether a linear combination of variables cointegrate to form a stationary equilibrium relationship.

4.2.1 The Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) Tests.

These test the null hypothesis of a unit root against the alternative of stationarity[3]. The simplest form of the Dickey-Fuller test estimates:

$$y_t = \rho_a y_{t-1} + \varepsilon_t \tag{4.6}$$

where y_t is the series, (y_t), and ε_t is a sequence of independent normal random variable with zero mean and variance σ^2, the null being H_0: $\rho_a = 1$ against the alternative H_1: $\rho_a < 1$. The standard approach to testing such a hypothesis is to construct a t-test; however, under non-stationarity, the statistic computed follow a Dickey-Fuller distribution. If the absolute value of ρ is less than one, then y_t converges to stationarity time series as t approaches infinity. In the case where y_t is stationary all of the roots of ρ lie outside the unit circle. If the absolute value of ρ is equal to one, y_t is then a random walk and is not stationary. In such a case the variance of y_t is $t\sigma^2$. Thus, as time increase the variance of y_t goes to infinite. If the series is nonstationary, ρ has unit or explosive root and all lie inside the unit circle. If the absolute value of ρ is greater than one, the variance of the series grows exponentially as t increase, and is once again nonstationary.

The standard approach to testing such a hypothesis is to construct a t-test. However, under non-stationarity the statistic computed does not follow a standard t-distribution but, rather, a Dickey-Fuller distribution. For each y_t a regression based on the above equation (4.6) is undertaken, with ρ_a now free to vary in order to compute the percentage of times the model will reject the null hypothesis of a unit root when the significance levels are based on the Dickey-Fuller distribution.

Testing for unit roots using the equation (4.6) involves making the prior assumption that the underlying d.g.p for y_t is a simple first order autoregressive process with a zero mean and no trend component. It also assumes that in the d.g.p time $t = 0$ and $y_t = 0$. This means using the regression equation (4.6) is only valid when the overall mean of the series is zero. Alternatively, if the true mean of the d.g.p were known, it could be subtracted from the observations and the equation (4.6)

---

[3]Again this section relies heavily on Harris (1995) and also Dickey and Fuller (1979).

could then be used to test for a unit root. However, this is unlikely to happen in practice. Nankervis and Savin (1985) have shown that by using equation (4.6) with $y_0 \neq 0$ can lead to problems of rejecting the null hypothesis of a unit root when the null is true, which would suggest that there are problems with the size of the test. Thus, when the underlying d.g.p is given by the equation (4.6) but it is not known whether y_0 in the d.g.p. equals zero, then it is better to allow a constant μ_b to enter the regression model when testing for a unit root:

$$\Delta y_t = \mu_b + (\rho_b - 1) y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim IID(0, \sigma^2). \tag{4.7}$$

The appropriate critical values to be used in this case are given by the Dickey-Fuller (DF) distribution relating to τ_ε since the latter was generated assuming that the underlying d.g.p. is given by (4.6) but the model used for testing is (4.7). Note, ρ_b and τ_μ are both invariant with respect to y_0 , that is, whatever the unknown starting value of the series, the distribution of the test statistic τ_μ is not affected. There is also a specific test statistic to use if an intercept and a linear time trend are included in the equation.

There is also an Augmented Dickey-Fuller test that is comparable to the simple DF test but involves adding $\Sigma\Delta y_{t-i}$ term to remove the serial correlation. This applies a non-parametric correction in order to take account of any possible autocorrelation. If a simple AR(1) DF model is used when in fact y_t follows an AR(p) process, then the error term will be autocorrelated to compensate for the mis-specification of the dynamic structure of y_t. Aurocorrelated errors will invalidate the use of the DF distributions. Assuming that y_t follows a pth order autoregressive process:

$$\Delta y_t = \gamma\, y_{t-1} + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + \ldots + \gamma_p \Delta y_{t-p+1} + \varepsilon_t \tag{4.8}$$

where, $\gamma = (\gamma_1 + \gamma_2 + \ldots + \gamma_p) - 1$. If $\gamma = 0$, against the alternative $\gamma < 0$, then y_t contains a unit root. To test the null hypothesis, we calculate the DF t-statistic (γ/se (γ)), which can be compared against the critical values. This is only valid in large samples. In small samples percentage points of the Augmented Dickey-Fuller (ADF) distribution are generally not the same as those applicable under the strong assumptions of the simple Dickey-Fuller model. As with the simple DF test, the above model needs to be extended to allow for the possibility that the d.g.p. contains deterministic components (constant and trend). The model needed to test for the null hypothesis of a stochastic trend (non-stationary) against the alternative of a deterministic trend (stationary) is as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \gamma y_{t-1} + \sum_{i=1}^{p-1} \gamma_1 \Delta y_{t-i} + \varepsilon_t \qquad \varepsilon_t \sim IID(0, \sigma^2) \tag{4.9}$$

where, Δy_t is the dependent variable, α_0 is a constant, and $\alpha_1 t$ is a time trend that captures growth. $\Sigma\gamma_1\Delta y_{t-i}$ is added to remove serial correlation, and ε_t is the error term. Therefore, it is very important to select the appropriate lag length; too few lags may imply some remaining autocorrelation and result in over-rejecting the null when it is true, while too many lags may reduce the power of the test, since unnecessary nuisance parameters reduce the effective number of observations available.

4.2.2 KPSS Test.

This section relies heavily on Kwaitkowski, Phillips, Schmidt, and Shin (1992). Many time series data contain a unit root. However, it is important to note that in the standard unit root tests such as ADF and DF tests, the null hypothesis is the presence of a unit root, and the way in which classical hypothesis testing is carried out ensures that the null hypothesis is accepted unless there is strong evidence against it. Therefore, the common failure to reject a unit root is simply that most time series data are not very informative about whether or not there is a unit root. The KPSS test provides a straightforward test of the null hypothesis of stationarity against the alternative of a unit root. It provides a plausible representation of both stationary and non-stationary variables, and which leads naturally to a test of the hypothesis of stationarity. Specifically, choosing a component representation in which the time series under study is written as the sum of a deterministic trend, a random walk, and a stationary error. The null hypothesis of trend stationarity corresponds to the hypothesis that the variance of the random walk equals zero. For almost all series we can reject the hypothesis of level stationarity, but for many of the series we are unable to reject the hypothesis of trend stationarity. It suggests that for many series the existence of a unit root is in doubt, despite the failure of Augmented Dickey-Fuller tests to reject the unit root hypothesis.

Consider the regression model below which a special case of Nabeya and Tanaka (1988) regression model. Let y_t, t = 1,2,...,T, be the observed series for which we wish to test stationarity.

$$y_t = \xi t + r_t + \varepsilon_t \qquad (4.10)$$

where, ξt is deterministic trend, ε_t is stationary error, and r_t is a random walk with $r_t = r_{t-1} + u_t$, where u_t is iid(0, σ^2_u) and r_0 is a fixed intercept. The stationarity hypothesis is simply $\sigma^2_u = 0$. Since ε_t is assumed to be stationary, under the null hypothesis y_t is trend stationary. However, if $\xi=0$ this is considered a special case. Note that the above model implies that $\Delta y_t = \xi + u_t + \Delta\varepsilon_t$. Defining $w_t = u_t + \Delta\varepsilon_t$ as the error in this expression for Δy_t. If u_t and ε_t are iid and mutually independent, w_t has a non-zero one period autocorrelation, with all other autocorrelations equal to zero, and accordingly it can be expressed as an MA(1) process:

$$w_t = \upsilon_t + \theta\upsilon_{t-1} \qquad (4.11)$$

The model $y_t = \xi + \beta y_{t-1} + w_t$, $w_t = \upsilon + \theta\upsilon_{t-1}$, $\beta = 1$, shows a connection between this test and the usual Dickey-Fuller tests. The Dickey-Fuller tests the hypothesis that $\beta = 1$ assuming $\theta = 0$; θ is a nuisance parameter. Dickey and Fuller (1979) states that the ADF tests are most commonly used to test the hypothesis of a unit root against the alternative of stationary, while Kwaitkoski et al (1992) design the KPSS model to test the hypothesis of stationarity against the alternative of a unit root. However, when comparing KPSS test with ADF test, we note that in the ADF test the null is the presence of a unit root (non-stationarity), while the KPSS test the null hypothesis is the absence of unit root (stationary). These two tests (KPSS and ADF) are testing the same thing but with different null hypotheses. The ADF test rejects the null for the series to be stationary in level, while the KPSS test will not be able to reject the null if it is going to be stationary.

Luintel (2001) pointed out that the ADF and KPSS tests are common and complementary tests for a unit root. Kwaitkowski et al (1992) indicate that the KPSS test is mainly relevant for annual data. The KPSS test has its limitations when using higher frequency data. Caner and Kilian (2001) provided results which are relevant to quarterly and monthly processes and they provided evidence that with roots close to unity, the use of asymptotic critical values may cause extreme size distortion. Caner and Kilian (2001) suggested that, when using higher than annual data frequency, the KPSS test has the tendency to reject the null of stationarity whether it is true or not, and they conclude that it is impossible to interpret rejections of the stationarity hypothesis in empirical work.

Meanwhile, according to Caner and Kilian (2001, p. 655) "it appears unlikely that any test of stationarity can ever be designed that completely overcomes the small-sample size distortion we can document and retains reasonable power, but additional research into the tradeoffs between alternative stationarity tests for a given sample size of interest is likely to help applied researchers to make an informed choice between alternative tests and to interpret test results obtained in practice". There is no one particular test that is the most accurate test for stationary in all situations, however, Lee and Amsler (1997) show that the KPSS statistic can distinguish consistently between short memory, stationary long memory, and either non-stationary long memory or unit root. Moreover, Lee and Schmidt (1996) show that the KPSS test is consistent against stationary long memory alternative.

4.3 COINTEGRATION.

The economic interpretation of cointegration is that if two or more series are linked to form an equilibrium relationship spanning the long-run, then even though the series themselves may be non-stationary they will nevertheless move closely together over time and the difference between them will be stationary (stable). The concept of cointegration mimics the existence of a long-run equilibrium to which the economic system converges over time, with ε_t as the disequilibrium error[4]. Thus cointegration processes define a long-run equilibrium for the variables, as they induce equilibrium correction which move the variables back towards its path. If these are cointegrated then regression analysis imparts meaningful information about long-run relationships and if they are not then there is the problem of spurious correlation, where a relationship is implied but all that is present is a correlation between the time trends. A test for cointegration can be thought of as a pre-test to avoid 'spurious regression' situations.

Testing for cointegration in this thesis is carried out using two methods. The first method is the Engle-Granger (1987) method. Harris (1995) indicated that if the testing is applied between two variables the Engle-Granger method produces unbiased estimates of the long run relationship. This is because the number of possible cointegration relationships increases with the number of variables, which implies an increasing ambiguity in determining the empirical validity of the method used. In the Engle-Granger method the cointegrating vector need not to be unique and also suggest that estimating the long-run parameters by estimating a dynamic regression rather than the static regression. In the case where there is no serial correlation in the error term, the t-statistic for testing the hypothesis has the standard normal distribution asymptotically. However, the disadvantage for this method is highlighted if the testing for cointegration is done for more than two variables.

The second method is the Phillips and Hansen (1990) approach. This method provides single equation estimates of cointegration relationship between non-stationary variables. This method applies nonparameteric corrections to the OLS estimator, whereas the ADF test modifies the

[4]The distance that the system is away from equilibrium at time t.

estimating equation. Phillips and Loretan (1991) noted that the FM-OLS and single equation ECM estimates are both substantially better than OLS. The performance of the ECM estimator is itself substantially improved by adding more lags, they also found that there are substantial size distortion in inference based on ECM estimates.

4.3.1 The Engle-Granger Cointegration Method.

In this thesis testing for cointegration is carried out between two variables, therefore applying the Engle-Granger Method would be suitable[5]. For series to be cointegrated, they must have comparable long-run properties. Consider two time series y_t and x_t, which must be differenced d times before they become stationary; thus said to be integrated of order d, and denoted I(d). If a linear combination of any two time series y_t and x_t is formed, and they are integrated of a different order, then the resulting series will be integrated at the highest of the two orders of integration. Thus if $y_t \sim I(1)$ and $x_t \sim I(0)$, then these two series will not be cointegrated as the I(0) series has constant mean while the I(1) series tends to drift over time and therefore, the error between them will not be stable over time. Hence, cointegration requires that if regressing y_t on x_t are both I(d) and there exists a vector β such that the disturbance term of a lower order of integration, I(d - b), from the regression ($\varepsilon_t = y_t - \beta x_t$), where $b > 0$, then Engle and Granger (1987) define y_t and x_t cointegrated of order (d, b). Thus, if y_t and x_t were both integrated of first order I(1), and $\varepsilon_t \sim I(0)$, then y_t and x_t would be cointegrated of order CI(1,1). The implication of this is that in order to estimate the long-run relationship between y_t and x_t then it is only necessary to estimate the statistical model:

$$y_t = \rho x_t + \varepsilon_t \qquad (4.12)$$

[5]The Engle-Granger Cointegration method discussion relies on Harris (1995) and Engle-Granger (1987).

Using OLS to estimate the above equation achieves a consistent[6] estimate of the long-run steady-state relationship between the variables in the model and all dynamics and endogeneity issues can be ignored asymptotically. This arises from what is called the superconsistency property of the OLS estimator when the series contegrated. To test the null hypothesis that y_t and x_t are not cointegrated amounts, in the Engle-Granger framework, to directly testing whether $\varepsilon_t \sim I(1)$ against the alternative that $\varepsilon_t \sim I(0)$. There are several tests that can be used, including the Dickey-Fuller and augmented Dickey-Fuller tests. Engle and Granger (1987) advocated ADF tests of the following:

$$\Delta\varepsilon_t = \gamma\,\varepsilon_{t-1} + \sum_{i=1}^{p-1}\gamma\Delta\varepsilon_{t-i} + \mu + \delta t + \omega_t \qquad \omega_t \sim IID(0,\sigma^2) \tag{4.13}$$

where the $\hat{\varepsilon}_t$ are obtained from estimating (4.12). The inclusion of trend and/or constant terms in the regression equation depends on whether a constant or trend term appears in equation (4.12). That is, deterministic components can be added to either equation (4.12) or (4.13) but not both. As with the testing procedure for unit roots generally, it is important to include a constant if the alternative hypothesis of cointegration allows a non-zero mean for $\hat{\varepsilon}_t$ (= $y_t - \beta x_t$), while in theory a trend should be included if the alternative hypothesis allows a non-zero deterministic trend for $\hat{\varepsilon}_t$. However, Hansen (1992) has shown on the basis of Monte Carlo experimentation, that irrespective of whether ε_t contains a deterministic trend or not, including a time trend in equation (4.13) results in a loss of power. Therefore, since it would generally be unlikely that $\hat{\varepsilon}_t$ from estimating equation (4.12) would result in a zero mean and given the results presented by Hansen, this form of testing for cointegration should be based on both equations (4.12) and (4.13) with δ set equal to zero.

Harris (1995) indicated that the I(1) variables asymptotically dominate the I(0) variable. The omitted dynamic terms and any bias due to endogeneity are captured in the residual which will consequently be serially correlated. According to Harris (1995), the Engle-Granger cointegration tests produce unbiased long-run relationship between two variables, but it may be at a

[6] That is as $T \rightarrow \infty$, the estimate of ρ converges to the true ρ. Any bias in finite samples should tend to zero as the sample size, T, tends to infinity.

disadvantage as the cointegrating variables increase to more than two. Moreover, according to Enders (1995, p. 385), it is possible to run the Engle-Granger test for cointegration by using the residuals from two different regressions, and as the sample size grows infinitely large, asymptotic theory indicates that the test for a unit root in one residual sequence becomes equivalent to the test for a unit root in the second residual sequence. The large sample properties on which this result is based may not be applicable to the sample sizes available to researchers. Further disadvantages of Engle-Granger method occur when reversing the order to a cointegrated variables, this is a very undesirable feature of the method since the test for cointegration should be invariant to the choice of the variable selected for normalization. This problem is compounded when there are more than two variables. Moreover, for more than two variables, there may be more than one cointegrating vector. The Engle-Granger method has no systematic procedure for the separate estimation of the multiple cointegrating vectors.

The Engle-Granger method is a two step method. The first step is to generate the error series and the second step uses the generated error to estimate a regression on the error term. Thus, the coefficient of the error term is obtained by estimating a regression using the residuals from another regression. Hence any error introduced in step 1 is carried into step 2. Some of these shortcomings are of lesser relevance to our two-variable situation.

4.3.2 Phillips and Hansen Cointegration Method

The limiting distribution of OLS estimators depend on two nuisance parameters, due to the long-run endogeneity of the regressors and due to serial correlation[7]. In order to eliminate the dependency on these nuisance parameters, Phillips and Hansen (1990) explore the asymptotic properties of instrumental variable estimates of multivariate cointegration regression and allow for deterministic and stochastic instruments. The method is based on transforming the variables from the estimates of the long-run relationship and its decomposition. The estimation techniques

[7]This section relies heavily on Phillips and Hansen (1990), Maddala and Kim (1998) and Pesaran and Pesaran (1997).

involve an extension of the fully modified (FM) regression procedure. For integrated regressors the individual stochastic trends of a set of instruments are sufficient to ensure that the relevance condition holds. Their focus was on multivariate cointegrating regression, the techniques employed in several tests such as cointegration.

The Phillips and Hansen (1990) Fully Modified (FM) OLS procedure applies non-parametric corrections to the OLS estimator to deal with the serial correlation. According to Banerjee, Dolado, Hendry, and Smith (1986) the superconsistency of OLS in cointegrating regressions was misleading in small samples. Their study demonstrated a poor approximation in sample sizes typical of economic data. However, Phillips and Hansen (1990) said that the superconsistency does not give any information on the sampling distribution and they also said that the asymptotic distribution theory is useful in small samples in choosing between different estimators and test statistics.

According to Phillips and Hansen (1990) the following linear regression model enables to estimation of the parameters of a single cointegrating relationship:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t, \quad t = 1, 2, \ldots, n \qquad (4.14)$$

where y_t is an I(1) variable, and x_t is I(1) regressors, assumed not to be cointegrated. It is assume that x_t has a first-difference stationary process:

$$\Delta x_t = \mu + v_t, \quad t = 2, 3, \ldots, n \qquad (4.15)$$

where μ is the drift parameter, and v_t is stationary variables. Assume that $\xi = (\varepsilon_t, v_t)$ is stationary with zero mean and a finite positive-definite covariance matrix. The OLS estimators of $\beta = (\beta_0, \beta_1)$ are consistent even if x_t and ε_t are contemporaneously correlated. In general, the asymptotic distribution of the OLS estimator involves the unit root distribution and is non-standard; carrying out inferences on β using the usual t-tests in the OLS regression will be invalid. This is one of the disadvantages of Engle-Granger method. The invalidity of the t-test in the OLS regression involving the unit-root distribution may be overcome using Phillips and Hansen FM-OLS estimators which take account of correlation between ε_t and v_t and their lagged value is required. Phillips and Hansen (1990) procedure provides single equation estimates of the cointegrating relationship between a set of I(1) variables. A set of I(1) variables are said to be cointegrated if a linear combination of them exists. A variable is said to be I(1) if it must be differenced once before it can be stationary.

4.4 BIVARIATE GARCH MODEL.

The increased importance played by risk and uncertainty considerations in modern economic and finance theory, initiated the development of new economic time series techniques that allow for the modelling of time varying variances and covariance. Volatility clustering is one of the most common observations concerning financial data in asset returns. Early research on time-varying volatility extracted volatility estimates from asset returns before specifying a parametric time series model for volatility. Officer (1973) estimated volatility at each point in time using a rolling standard deviation where the standard deviation of returns measured over a sub-sample which moves forward through time. Meanwhile, Garman and Klass (1980), and Parkinson (1980) have used the difference between the high and low prices on a given day to estimate volatility for that day. Such methods assume that volatility is constant over some interval of time. These methods are often quite accurate if the objective is simply to measure volatility at a point in time. However, volatility can be estimated arbitrarily accurately with an arbitrarily short sample period if one measures prices sufficiently frequently. A basic observation about volatility clustering implies large (small) changes tending to be followed by large (small) changes of random sign leading to unconditional non-normality. In other words, the volatility of asset returns appears to be serially correlated. Also in the engagement in forecasting financial time series, e.g. stock prices, researchers have observed that their ability to forecast such variables varies considerably from one period to another. For some time periods the forecast errors are relatively small (large), then they are small (large) again for another time period. This variability could very well be due to volatility in financial markets suggesting that the variance of forecast errors is not constant but varies from period to period, indicating the existence of some kind of autocorrelation in the variance of forecast errors. The behaviour of disturbances (ε_t), and the apparent lack of any structural dynamic economic theory may explain the variation in higher order moment, to capture the volatility and correlation. While conventional time-series and economic models operate under as assumption of constant variance, the Autoregressive Conditional Hetreoskedastic (ARCH) class of models introduced by Engle (1982) captures the serial correlation of volatility allowing the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. The success of the ARCH model lies in the fact that these models are able to capture the volatility clustering and unconditional non-normality in financial data, and their similarity with standard time series techniques used to estimate the conditional mean. The multivariate ARCH model is useful in numerous applications and diverse areas.

This section relies heavily on Choudhry (1999) and Wahab (1995). As stated earlier that the GARCH model may be applied both in univariate and multivariate forms. The univariate form utilizes only the information in one market's own history, while the bivariate GARCH model uses information from more than one market's history. The mulivariate GARCH provides estimates of the parameters taking into account any inter-market dependence in the conditional moments of the joint distribution. The GARCH model utilizes information in the entire variance-covariance matrix of asset price changes, which depends on elements of the information set. Bollerslev (1986) mentioned two restrictions in dealing with estimation of bivariate GARCH models. The first restriction assumes that variances follow a GARCH process, while the second assumes that covariances vary to keep the correlation matrix constant. Furthermore, diagonal restriction is to allow for time-varying conditional correlation on the bivariate GARCH parameters matrices in order for each variance and covariance element to depend only on its own past values and prediction errors.

According to Engle and Kroner (1995), bivariate GARCH models require the modelling of both variance and covariance. The variance and covariance depend on the information set in the ARMA model. Therefore, the extension from univariate GARCH model to a multi-variate model requires allowing the conditional variance and covariance matrix of the n-dimensional zero mean random variables ε_t to depend on elements of the information set Ω_{t-1}. In the bivariate GARCH process in the diagonal representation in which each element of the covariance matrix, $h_{jk,t}$, depends only on past own squared residuals, and covariances depend only on past own residuals.

This seems to be a plausible restriction because information about variance is usually revealed in squared residuals.

According to Choudhry (1999), the bivariate GARCH (p, q) model used to represent the returns from the stock cash and futures markets may be expressed as follows:

$$y_t = \alpha_i + \varepsilon_t - \theta_i \varepsilon_{t-1} \tag{4.16}$$

$$\varepsilon_t / \Omega_{t-1} \sim N(0, H_t) \tag{4.17}$$

$$vech(H_t) = C + \sum_{j=1}^{p} A_j \, vech(\varepsilon_{t-j})^2 + \sum_{j=1}^{q} B_j \, vech(H_{t-j}) \tag{4.18}$$

where $y_t = (r_t^c, r_t^f)$ is a (2x1) vector containing stock returns from the cash and futures markets; α_i is the mean of the stock returns; $\theta_i \varepsilon_{t-1}$ is the moving average term (MA);H_t is a (2x2) conditional covariance matrix; C is a (3x1) parameters vectors (constant); A_j and B_j are (3x3) parameter matrices; and vech is the column stacking operator that stacks the lower triangular portion of a symmetric matrix. The following presents a diagonal vech bivariate GARCH (1, 1) conditional variance equations[8]:

$$H_{11,t} = C_1 + A_{11}(\varepsilon_{1,t-1})^2 + B_{11}(H_{11,t-1}) \tag{4.19}$$

$$H_{12,t} = C_2 + A_{22}(\varepsilon_{1,t-1}\varepsilon_{2,t-1}) + B_{22}(H_{12,t-1}) \tag{4.20}$$

$$H_{22,t} = C_3 + A_{33}(\varepsilon_{2,t-1})^2 + B_{33}(H_{22,t-1}) \tag{4.21}$$

In the bivariate GARCH (1,1) model, the diagonal vech parameterization involves nine conditional variate parameters. The values C, A_{11}, A_{33}, B_{11}, and B_{33} are restricted to zero or greater to ensure a positive conditional variance. The MA term ($\theta_i \varepsilon_{t-1}$) is added to capture the non-synchronous trading. The ARCH process in the residuals from the cash equation is shown by the coefficient of $(\varepsilon_{1,t-1})^2 (A_{11})$, while the coefficients of $(\varepsilon_{2,t-1})^2 (A_{33})$ present the ARCH process in the futures equation residuals. The parameters, A_{22} and B_{22} represent the covariance GARCH parameters, which account for the conditional covariance between cash and futures prices. Significant covariance parameters imply strong interaction between the cash and futures prices. It is vital to let conditional covariance be time-dependent. This ability of the bivariate GARCH

[8]Most studies claim that for stock market data, the GARCH(1,1) model is sufficient.

model to have time-dependent conditional variance makes it ideal to provide a time-varying hedge ratio. If $A_{11} + B_{11}$ and $A_{33} + B_{33}$ are both less than unity then $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are covariance stationary, respectively. Meanwhile, if $A_{11} + B_{11}$ and $A_{33} + B_{33}$ are both equal to 1 then the current shock persists over a long period of time in conditioning the future variance of the return from the cash and futures markets, respectively. Since shocks persist over long periods of time then the impact of volatility on the stock prices is significant.

Since the introduction of stock index futures markets in the early 1980s, several studies have investigated the optimal hedge for stock market portfolio using the stock index futures. Recent studies find that the time dependent conditional variance model improves the hedging performance in various futures contract.[9] The bivariate GARCH model takes into consideration the time-varying distribution of the cash and futures price changes, and provides a time-varying hedge ratio. The bivariate GARCH hedge ratio is expected to provide greater reduction of risk in futures markets. The advantage of the bivariate GARCH specification is that very convenient assumptions about the conditional density of commodity prices changes, can lead to a rich model that allows for time dependent conditional variances in the unconditional distribution of price changes. Another advantage of the bivariate GARCH model is incorporating heteroscedasticity into the estimation procedure and it also captures the tendency for volatility clustering in financial and economic data. From the bivariate GARCH model of the cash and futures stock returns presented earlier, the time-varying hedge ratio can be expressed as:

$$\beta_t = \hat{H}_{12,t} / \hat{H}_{22,t} \tag{4.22}$$

where $\hat{H}_{12,t}$ is the estimated conditional covariance between the cash and futures stock returns and $\hat{H}_{22,t}$ is the estimated conditional variance of the futures returns from the bivariate GARCH model. Since both $\hat{H}_{12,t}$ and $\hat{H}_{22,t}$ are time-varying, the hedge ratio β_t will also be time-varying.

[9]See section 3.5 of chapter 3.

4.5 The BIVARIATE GARCH-X MODEL.

The Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model has many different applications. According to Chou (1988) the GARCH model provides a more flexible framework to capture various dynamic structures of conditional variance and allows simultaneous estimation of parameters and hypotheses. Since then Lee (1994) followed that by extending the GARCH model by linking it to the error correction model (ECM) of Cointegrated series. This model is called GARCH-X model, which testes long-run equilibrium relationship of integrated series and can be used for types of equilibrium into time series models. Engle and Yoo (1987) show that the error correction (ECM) term, the short-run deviation from a long-run cointegration relationship has important predictive power for conditional mean of the cointegrated series. Taking this into consideration, Lee (1994) examined the behaviour of the variance over time as a function of short run deviation, as an increase in volatility is expected due to shocks to the system which propagate on both the mean and variances. An extended bivariate GARCH model with error correction term for the variance is used. Thus, the GARCH-X model takes into consideration the long run relationship between two or more markets. According to Lee (1994) the GARCH-X examines the potential relationship between disequilibrium and uncertainty in the cointegration system. If the cash and futures prices are cointegrated then the error correction term from the cointegration relationship can be applied in the bivariate GARCH model. In this dissertation the GARCH-X model is used to estimate the optimal hedge ratio for several time series taking into consideration the long run cointegration relationship between the cash and future prices. The following section relies heavily on Choudhry (1997) in expressing the following bivariate GARCH (p,q)-X model of the returns from the stock cash and futures returns:

$$y_t = \alpha_i + \varepsilon_t - \theta_i \varepsilon_{t-1} \tag{4.23}$$

$$\varepsilon_t / \Omega_{t-1} \sim N(0, H_t) \tag{4.24}$$

$$vech(H_t) = C + \sum_{j=1}^{p} A_j \, vech\,(\varepsilon_{t-j})^2 + \sum_{j=1}^{q} B_j \, vech\,(H_{t-j}) + \sum_{j=1}^{K} D_j \, vech\,(z_{t-j})^2 \tag{4.25}$$

where $y_t = (r^c_t, r^f_t)$ is a (2x1) vector containing stock returns from the cash and futures markets, α_i is the mean of the stock returns; $\theta_i\ \varepsilon_{t-1}$ is the moving average term (MA); H_t is a (2x2) conditional covariance matrix, C is a (3x1) constant parameter vector, A_j and B_j are (3x3) parameter matrices, vech is the column stacking operator that stacks the error correction term (short-run deviations) from the long-run cointegration relationship, and D_j is a (3x3) matrix. The size and significance of the parameters, D_j, indicate the relationship between short-run deviations and conditional variance. A parsimonious representation is obtained while a number of restrictions may be imposed by assuming that A_j and B_j are diagonal restrictions on the multivariate GARCH parameter's matrices.

The following equations represent diagonal vech bivariate GARCH (1, 1)-X conditional variance equations with k equal to 1 and the squared error-correction term (Z_t) lagged once (Choudhry (1997)).

$$H_{11,t} = C_1 + A_{11}(\varepsilon_{1,t-1})^2 + B_{11}(H_{11,t-1}) + D_{11}(Z_{t-1})^2 \tag{4.26}$$

$$H_{12,t} = C_2 + A_{22}(\varepsilon_{1,t-1}\ \varepsilon_{2,t-1}) + B_{22}(H_{12,t-1}) + D_{22}(Z_{t-1})^2 \tag{4.27}$$

$$H_{22,t} = C_3 + A_{33}(\varepsilon_{2,t-1})^2 + B_{33}(H_{22,t-1}) + D_{33}(Z_{t-1})^2 \tag{4.28}$$

From the above equations there are nine conditional variance parameters. Once again the values of C, A_{11}, A_{33}, B_{11} and B_{33} are restricted to zero or greater to ensure a positive conditional variance. As in the GARCH model the ARCH process in the residuals from the cash equation is shown by the coefficient on $(\varepsilon_{1,t-1})^2$ (A_{11}) and the ARCH process in the futures equation residuals is presented by the coefficient on $(\varepsilon_{2,t-1})^2$ (A_{33}). The parameters A_{22} and B_{22} represent the covariance GARCH parameters.

The parameters D_{11} and D_{33} indicate the effects of the short run deviations between the cash and futures prices from long run cointegrated relationship on the conditional variance and the conditional covariance. According to Lee (1994) the stock prices become more volatile and harder to predict as the spread between the two prices gets larger. In such case, the squared error correction terms have a positive effect on the conditional variance. On the other hand, a significant negative effect indicates that an increase in the spread between the spot and futures prices reduces the volatility. Therefore, the existence of the short run deviations in the conditional variance function could be used for a point forecast of stock price changes. The GARCH-X model is used in this research study to estimate the time varying optimal hedge ratio. The bivariate

GARCH-X model provides a time varying hedge ratio taking into consideration the cointegration relationship between cash and futures markets which can be written as:

$$\beta_t = \widehat{H}_{12,t}/\widehat{H}_{22,t} \tag{4.29}$$

The $\widehat{H}_{12,t}$ and $\widehat{H}_{22,t}$ are defined as before. Once again the hedge ratio is time-varying.

4.6 Out-of-Sample Testing

In order to investigate the out-of-sample effectiveness of the hedging methods used in the thesis, the time-varying and minimum variance equation is estimated for fixed time periods shown in the diagrams below. Subsequently, the estimated fixed parameters are applied to generate the conditional variance and covariance of the daily out-of-sample time period as indicated by Baillie and Myers (1991), Park and Switzer (1995) and Choudhry (1999). Although, the hedge ratios of the within-sample periods for stock and commodity markets are expected to perform better, the out-of-sample results demonstrate what might be expected from practical implementation of the hedging strategy over the long run.

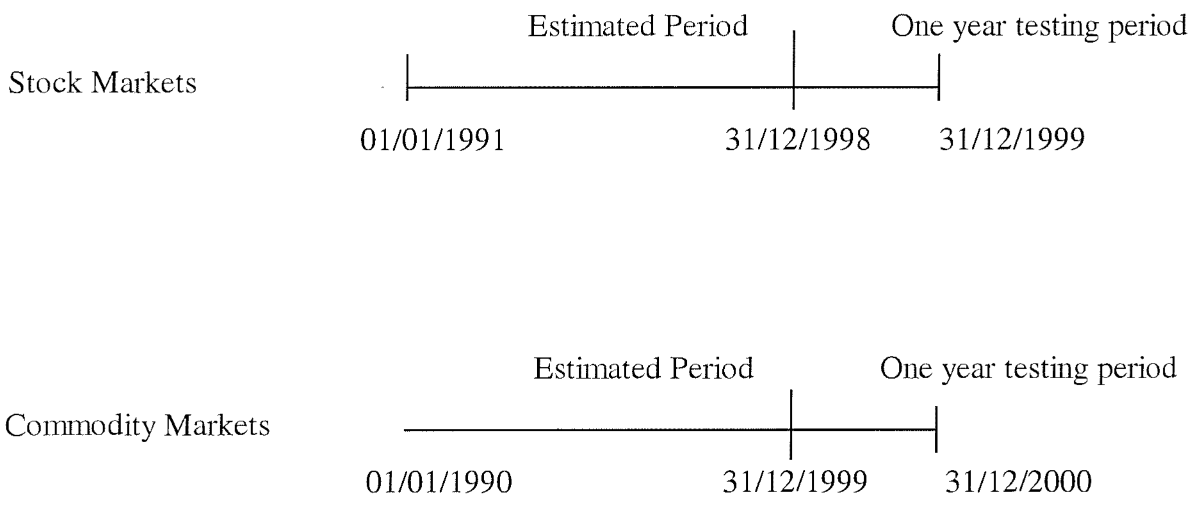


Figure 4.1

Portfolio managers may use the out-of-sample period in order to test the performance of the hedge ratio for a certain period. For the one year out-of-sample period, as shown in the above Figure 4.1 the parameters are estimated for the periods January 1991 to December 1998 and January 1990 to December 1999 for stock and commodity markets respectively, in order to set the hedge ratios for the one year out-of-sample time period. The one year out-of-sample daily generated hedge ratios are for the period 1st January 1999 to 31st December 1999 and 1st January 2000 to 31st December 2000 for the stock and commodity markets, respectively. The performance during each particular sample period in terms of variance reduction is discussed in sections 5.2.1 and 6.2.1.

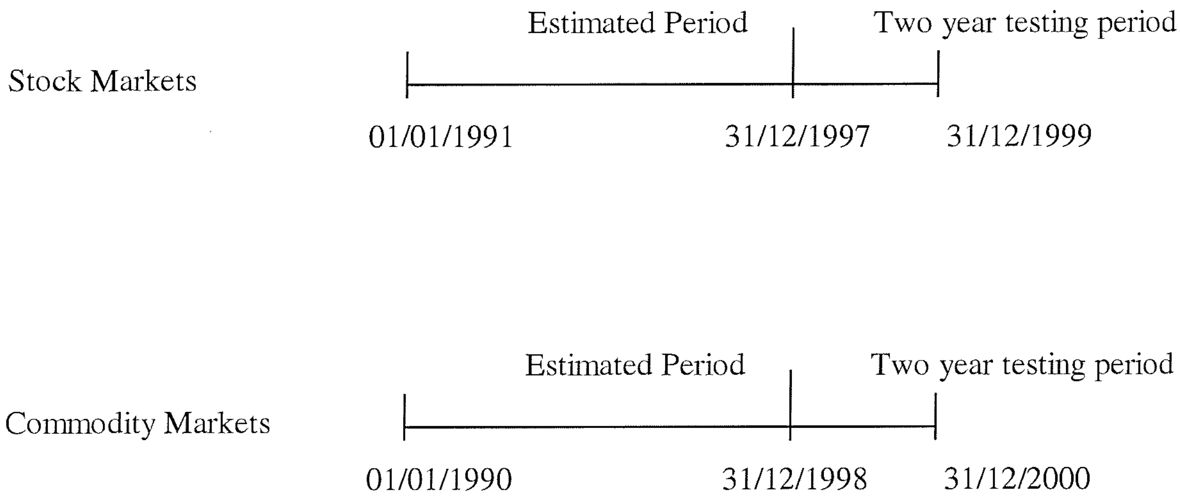


Figure 4.2

From the Figure 4.2 above for the two years out-of-sample time period, the parameters are estimated for the periods of January 1991 to December 1997 and January 1990 to December 1998 for the stock and commodity markets, respectively. Again, the performance for the two year out-of-sample time period is discussed in 5.2.2 for stock markets and in 6.2.2 for the commodity markets.

The applications of two different out-of-sample time periods for both stock and commodity markets were carried out to create a way to generate the hedge ratio for a particular period of time indicated for risk reduction purposes. Different out-of-sample tests are also conducted in order to establish whether changing the length of out-of-sample time period indicates changes in the results. This is relevant for the portfolio manager to investigate the performance expected during any particular sample. This gives an indication of how the frequency of re-estimation of hedge ratios might affect subsequent hedging performance, in practice.

4.7 Conclusion.

This dissertation applies the classical regression method to estimate the constant minimum hedge ratio. The dissertation further applies the GARCH and GARCH-X models to estimate time-varying hedge ratios. The cointegration test between cash index and futures index is conducted by means of the Engle-Granger and Phillips-Hansen methods. Out-of sample tests are used to demonstrate what might be expected from practical implementation of the hedging strategy over the long run. The next two chapters discuss the empirical results from applying these methods in the stock index and commodity markets.

CHAPTER FIVE

5.0 EMPIRICAL RESULTS FROM STOCK MARKETS.

5.1 WITHIN-SAMPLE TIME PERIOD RESULTS.

5.1.1 Stock Index Cash and Futures Data.

The data used in the empirical analysis of stock index futures markets ranges from the 1st January 1991 to 31st December 1999 for each series. Daily data from seven major stock index futures markets from seven different countries are applied. The countries are Australia, Germany, Hong Kong, Japan, South Africa, UK, and US. The data is obtained from DATASTREAM. The cash return and futures return are simply the first difference of the log of the price index. The table below indicates each of the stock indices for the futures markets under investigation.

Table 5.1

Cash and Futures indices

Country	Cash Index	Futures Index
Australia	Australia SE All Ordinary	SFE - All Ordinaries SPI
Germany	DAX 30 Performance	EUREX-DAX
Hong Kong	Hang Seng	HKFE - Hang Seng
Japan	Nikkei 225	Nikkei 225 Stock Average
South Africa	SA(RDM)-Industrial	SAFEX- Industrial 25
United Kingdom	FTSE 100	FTSE 100
United States of America	S&P 500 Composite	CME- S&P 500

The Australian spot stock index is based on the All Ordinary Price Index and the futures price index is based on the All Ordinary Futures Index. The All Ordinary Share Index contains 307 Australian stocks. The spot and futures prices of the Hong Kong indices are based on the Hang Seng price index and Hang Seng futures, respectively. The Hang Seng Index contains 33 stocks on the Hong Kong stock exchange. The Nikkei 225 contains 225 Japanese stocks, with the Nikkei 225 price index used for the cash price index and Nikkei 225 stock average futures price used for the futures index. Both of the UK spot and futures indices are based on the FTSE 100, which is based on the quoted UK companies with the largest market capitalisation. The S&P 500 index futures are traded on the Chicago Mercantile Exchange (CME), with the spot index based on the S&P 500 composite. All futures price indices are continuous series. The continuous series starts at the nearest contract month which forms the first values for the continuous series until the contract reaches its expiry date. At this point the next trading contract month is taken. Care is taken to ensure that all calculated futures returns are based on prices from contracts with the same delivery date.

Basic statistics for the fourteen cash and futures stock returns are shown in Table 5.2. All series have positive and significant kurtosis. All cash returns are leptokurtic except for Japan and the UK where they are platykurtic. Again all series of futures returns are leptokurtic except Japan and the UK. The Hong Kong, Japan, and the UK cash and futures series are skewed to the right, while the rest of series are skewed to the left. The Australian cash index has the lowest variance, while the Hong Kong futures returns has the highest variance.

5.1.2 Unit Root Tests.

5.1.2.1 Augmented Dickey-Fuller (ADF) Test Results.

The first tests conducted are for the presence of unit roots in all seven cash and futures price indices and returns. Tests for stationarity and non-stationarity are carried out using Augmented Dickey-Fuller (ADF) tests discussed in section 4.2.1 of chapter 4. In other words, the ADF tests for first order integration and second order integration. A first order integrated process contains one unit root and a second order integrated process contains two unit roots. The following equation represents the ADF test.

$$\Delta y_t = \alpha_0 + \alpha_1 t + \beta y_{t-1} + \gamma_i \sum_{i=1}^{p-1} \Delta y_{t-i} + \varepsilon_t$$

where, Δy_t is the dependent variable, α_0 is a constant, t is a time trend to capture the growth, ε_t is the error term and $\Sigma\Delta y_{t-i}$ term is added to remove the serial correlation. In this test, for the series to be stationary the coefficient (β) has to be negative and significant. In other words the coefficient on y_{t-1} should be negative and significant in order to reject the null hypothesis of the unit root. The first order integration is tested with trend to capture the growth of the price index and the second order integration is tested without trend where the growth is constant. The first order integration is testing for trend stationarity, and the second order integration is testing for stationarity around the mean[1]. The ADF test includes lags of the dependent variable in order to reduce serial correlation. The ADF tests start with the maximum 15 lags and then lags are reduced by 3 each time. Results with the lowest number of lags with no serial correlation are presented. The ADF test with no lags is simply the Dickey-Fuller test (DF). Table 5.3 shows the ADF test results. In the case of the Australian first order integration test the coefficient is negative and

[1]The trend in the first order integration ADF test makes the null hypothesis that the d.g.p contains a stochastic trend against the alternative of trend stationary. If a d.g.p contains a deterministic trend component and the first order integration ADF test is conducted without a trend, it may falsely accept the null of stochastic trend (Harris, 1995).

significant. This implies that the Australian price index is stationary in levels. This is true of both the cash and futures price indices. Results in Table 5.3 also indicate that Australian cash returns and futures returns are also stationary (two root test). However, for the rest of the first order integration tests, we found that all the coefficients are negative and not significant. Meanwhile, the second order integration tests results show negative and significant coefficients. This implies all the cash and futures price indices are non-stationary in levels and stationary after first difference, except in the case of Australia where both prices of cash and futures indices are stationary in levels and after first difference. As a result of the Australian prices and in order to confirm the ADF results a second unit root test, which is called the KPSS test is employed.

5.1.2.2 KPSS Test Results.

The KPSS test is applied to check for both first order integration and second order integration. This provides a test of the null hypothesis of stationarity against the alternative of a unit root (non-stationary). Once again the first order integration is tested with a trend and the second order integration is tested without the trend[2]. Both the first order integration and second order integration results are presented for 0, 3, 6, 9, 12, and 15 lags. The ADF test found the Australian cash and futures prices to be stationary in levels and after first difference (see Table 5.3). However, in the KPSS tests the null hypothesis of stationarity is rejected at all lags for the Australian cash and futures prices and accepted for the cash and futures returns. Table 5.4 shows that the Australian cash price index and futures price index are non-stationary in levels and stationary after first difference. Meanwhile, as shown in Tables 5.5 to 5.10, every other cash and futures price series is found to be non-stationary in levels and stationary after first difference. In other words the KPSS tests reject the null hypothesis of trend stationarity for every series at all lag lengths. However, it is unable to reject the null hypothesis of stationarity after first difference. By testing both the unit root hypothesis and the stationarity hypothesis, we can distinguish the series which appear to be stationary from those with a unit root(s), and series for which the data

[2]The null hypothesis of first order integration KPSS test is trend stationary against the alternative of a stochastic trend.

are not sufficiently informative to be sure whether they are stationary or non-stationary. The KPSS tests are intended to complement the ADF unit root tests. The KPSS test backs up the ADF results for every series involved in our data except for Australia. Given that KPSS is a more robust test than the ADF, these results confirm that all of the data tested are non-stationary in levels and stationary after first difference.

5.1.3 Ordinary Least Squares (OLS) Results.

The OLS method is applied to estimate the minimum variance hedge ratios. The following relationship is estimated by means of OLS:

$$r_t^c = \alpha + \beta\, r_t^f + \varepsilon_t$$

r_t^c is the return in the cash market and r_t^f is the return in the futures market. The coefficients α and β show the relationship between cash and futures returns. The latter (β) is the optimal hedge ratio and can be expressed as:

$$\beta_{t-1} = Cov(r_t^c, r_t^f)/Var(r_t^f).$$

Where Cov is the covariance between the cash and futures returns and the Var is the variance of the futures return. The significance of the parameters will be tested by the t-test. Given that all cash and futures returns are found to be stationary, OLS regression between r_t^c and r_t^f is econometrically sound. Table 5.11 presents the OLS results. In all seven tests the relationship between cash and futures returns is direct and significant. For example, the coefficient on futures returns in the Australian market is 0.6886 which is less than one and significant at less than the 1% level. This result implies that a 1% change in the futures return brings about 0.6886% change in the cash return. If the futures market has the same or higher price volatility than the cash market, then the hedge ratio can be no greater than the correlation between them, which will be less than unity. The value of the hedge ratio is less than unity, so that the hedge ratio that minimises risk in the absence of basis risk turns out to be dominated by β when basis risk is taken into consideration. In all the results we find that β is less than one, where β is the minimum variance hedge ratio[3]. Japan has the highest β at 0.934 and South Africa has the lowest β at 0.6285. In other words, Japan has the highest and South Africa has the lowest minimum variance hedge ratios. The closer the value of β to one the closer is the hedge to being perfect, where no risk exists. The perfect hedge implies there is a one-to-one relationship between cash and futures prices. The constants are significant in all the cases except in Hong Kong and Japan. The R^2 is relatively large and ranges between 0.9194 in the case of the US to 0.6525 in the case of Germany. The R^2 results imply that in the US test 91% of the movement in the dependent variable is explained by the independent variable, leaving just 9% of the relationship unexplained by the independent variable. In all tests the values of the Durbin-Watson (DW) statistic are greater than two, therefore negative serial correlation may exist[4].

5.1.4 The Bivariate GARCH (1, 1) Results.

The Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model expresses the conditional variance as a linear function of past values of squared disturbance and conditional variance. According to Mandelbrot (1963) and Fama (1965), volatility clustering is seen as large (small) changes in stock prices followed by large (small) changes of either sign, and small (large) changes in stock prices followed by small (large) changes of either sign. As most stock returns are non-normally distributed, this confirms that the unconditional distributions of stock return changes to be leptokurtic, skewed, and volatility clustered. The GARCH models are capable of

---

[3]Additional tests were carried out to investigate whether $\beta = 1$ or $\beta \neq 1$, the results show that in all cases the null hypothesis ($\beta=1$) is rejected.

[4]Negative serial correlation exists when the value of the Durbin-Watson statistic is greater than 2, while positive serial correlation exists if the value of the Durbin-Watson statistic is less than 2. Serial correlation occurs as shocks in stock markets persist over long periods of time. The negative serial correlation observed could affect the standard errors and t-ratio in the OLS regression but not the slope coefficient (β), hence there is no need to take corrective action in this particular case.

capturing the dynamic structures in stock return data.

Tables 5.12 and 5.13 present the bivariate GARCH (1,1) estimation for the seven countries[5]. Previously, Bollerslev et al. (1992) indicated that GARCH (1,1) is sufficient for most financial series. From Tables 5.12 and 5.13 a significant ARCH is found in all cash and futures tests. The sizes of the ARCH parameters A_{11} (cash market) and A_{33} (futures market) are significant and less than unity in all cases. This indicates volatility clustering in these markets. The ARCH coefficients in the residuals for the cash equation range from 0.0727 in the case of Australia to 0.169 in the case of South Africa. Meanwhile, the lowest ARCH coefficients in the futures equation is 0.0785 in Australia and the highest is 0.146 again in South Africa. The higher the ARCH coefficient the higher the volatility. The coefficients of B_{11} and B_{33} are positive in all cases and their significance expresses the existence of the GARCH effect which indicates the impact of past variance. Noticeably, in all cases all of the persistence measures (A_{11} + B_{11}, A_{33} + B_{33}) for the cash and futures markets involved are less than one. The persistence measures for the cash markets range between 0.8536 (UK) and 0.9612 (Germany). This indicates that the German markets show the highest persistence of shocks to volatility and the UK markets the lowest persistence. The persistence measures in the futures markets range between 0.8623 in the case of Australia and 0.9635 in Hong Kong.

Low persistence implies that the persistence of volatility would die down after a short period of time in the cash and futures indices, therefore the shocks are not explosive and the conditional variance in this situation is stationary. According to Poterba and Summers (1986), a significant impact of volatility on the stock prices occurs only if shocks to volatility persist over a long time. Alternatively, stock prices are not affected by volatility movement if shocks to volatility are brief. Significant and positive covariance GARCH parameters (A_{22} and B_{22}) represent strong interaction between the cash and futures prices in all markets. From Tables 5.12 and 5.13, all covariance parameters are significant and positive. These tables also show a significant MA terms (θ_1 and

[5]All GARCH and GARCH-X models are estimated by means of the Berndt, Hall, Hall, and Hausman (1974) method. The specification of the models is presented in sections 4.4 and 4.5 of chapter 4.

θ_2) which may be due to non-synchronous trading[6]. Non-synchronous trading effect arises when prices are taken to be recorded at time interval of one length when in fact they are recorded at time intervals of other irregular length. The MA terms are positive in all cases except in the South Africa cash return, where it is negative. The non-synchronous effect induces potentially biases in the mean, variance, covariance and autocorrelation coefficients. According to Scholes and Williams (1977) non-synchronous trading induces negative serial correlation.

As pointed out by Giannopoulos (1995) the lack of serial correlation in the standardized residuals and the standardised squared residuals implies that there is no need to encompass a higher-order ARCH process[7]. Table 5.14 presents the Ljung-Box statistics concerning the standardised squared residuals in order to detect the presence of a higher ARCH order. The order of 6 lags are presented in the tables showing no serial correlation for both cash and futures series in most cases, except for the Australian and the US series where both cash and futures series show serial correlation at less than the 5% level[8]. These results may indicate that the GARCH (1,1) model used in this particular research is suitable with no need to encompass a higher order ARCH process.

[6]Non-synchronous trading may only apply to the cash indices.

[7]Only standardised squared residuals results are shown in tables for test for higher order ARCH effect.

[8]Serial correlation was also tested for higher order lags. In all cases including the USA case no serial correlation is shown at higher order.

5.1.4.1 Comparison of Hedge Ratios.

In this section, four different types of hedging methods are compared for their hedging effectiveness within the total sample period. As stated in chapter 4, the bivariate GARCH model provides a time-varying hedge ratio. For the other methods, the hedge ratios remain constant. The comparison between the hedging effectiveness for the unhedged, traditional[9], minimum variance (OLS), and GARCH models hedge ratios are carried out by constructing portfolios implied by the computed hedge ratios and then comparing the variance of these constructed portfolios. In order to compare the performance of each type of hedge, the portfolios are constructed as (r^c_t - β_t* r^f_t) where r^c_t is the cash returns, r^f_t is the futures returns and β_t is the estimated optimal hedge ratio[10]. The smaller the variance, the more effective is the hedge ratio.

Table 5.15, part A shows the variance of portfolios and part B shows the percentage change in variance of portfolios estimated using the GARCH hedge ratio relative to the other hedge ratios for the within-sample period used in this study. The change in variance is calculated as (Var_{others} - Var_{GARCH})/Var_{other}. The comparison of changes in variance is conducted only between the time-varying hedge ratio portfolios estimated by the GARCH model and constant hedge ratios portfolios estimated by means of unhedged, traditional, and minimum variance hedge ratio methods. The performance of the time-varying hedge methods versus the constant methods is indicated by whether the percentage change in variance is negative or positive. The investor is advantaged by the time-varying hedge if the percentage change is positive. However, the investor is disadvantaged if the percentage change in variance is negative.

From Table 5.15 the GARCH based hedge ratio provides the lowest variance portfolio in comparison to the unhedged and traditional variance portfolios for each country except in the case of Japan where the traditional hedge outperforms the GARCH portfolio. The GARCH portfolio reduces the variance by a high percentage compared to both the unhedged and traditional

[9]See section 2.4.1. of chapter 2.

[10]In the constant hedge ratio cases the β does not have a time script.

portfolios for most cases. However, the reductions in the variance between the GARCH ratio portfolio and the minimum variance portfolio varies noticeably. In comparison to the minimum variance hedge, the GARCH hedge ratio provides the lowest variance portfolio in Australia, Hong Kong and South Africa. Thus, minimum variance constant ratio portfolios provides the lowest variance and outperforms the GARCH portfolio in the other cases. The reduction in the variance of the portfolio using the minimum variance constant ratio compared with the time-varying GARCH ratio is small in the cases of Germany and the UK. Meanwhile, the percentage changes in variance of the minimum variance hedge are more than 10% and 5% in the cases of the US and Japan, respectively. The GARCH ratio compares well against the unhedged and traditional methods and also compares favourably against the minimum variance method in some cases. GARCH hedge provides the lowest variance portfolios for Australia, Hong Kong and South Africa against all the constant hedge ratios. As Baillie and Myers (1991) suggested, the additional complexity of a GARCH model will be justified by superior hedging performance for some commodities but not others. It appears that no generalisations are possible, and the performance of alternative hedging rules will have to be examined on a case-by-case basis.

Portfolio managers increase/decrease the size of the investment in the stock market by buying/selling index futures. Portfolio managers may have to make frequent and sometimes substantial adjustment to the portfolio when the optimal hedge ratio changes by some fixed amount (Park and Switzer, 1995). However, the transaction cost may be too high to frequently adjust the portfolios according to a time-varying optimal hedge ratio. From Table 5.15, the GARCH model reduces risk marginally and by less than 3% in cases of Australia, Hong Kong and South Africa, but is outperformed in the other cases compared to the minimum variance method. This indicates that the portfolio manager may hedge their risk using the minimum variance method as the drop in the variance using GARCH method is small, advocating that the transaction cost may be too costly. However, they may hedge using the GARCH method when compared to the unhedged and traditional methods, as the drop in variances are more substantial. Overall, this evidence is not convincingly in favour of employing a time-varying GARCH hedge ratio.

5.1.5 Cointegration Results.

5.1.5.1 Engle-Granger Method.

Changes in prices in one market (cash or futures) may bring about price changes in the other market. This brings about a long-run equilibrium relationship which can be presented by the following equation:

$$S_t = \alpha + \beta F_t + \varepsilon_t$$

where S_t and F_t are log of cash and futures prices at time t and both variables are I(1); α and β are parameters; and ε_t is the error term. Ordinary Least Squares (OLS) is inappropriate if S_t and F_t are non-stationary because the standard errors are not consistent. The earlier section on unit roots showed the price indices to be non-stationary in levels. The inconsistency disallows hypothesis testing of the parameter (β). Under such conditions, cointegration constitutes a better method. Testing for cointegration is based on checking for unit root(s) in the residual of the regression equation above. The Engle and Granger method[11] for the above regression is carried out in two steps; the first step is to run the OLS regression between S_t and F_t, and the second step applies the unit root test (the ADF test) to the error term of the regression. If the error term does contain unit roots then S_t and F_t are not cointegrated. However, if the error term does not contain unit roots then S_t and F_t are cointegrated, indicating that S_t and F_t have a long-run equilibrium relationship. If the error term contains one unit root, it is a first order integrated process and if it contains two unit roots, it is a second order integrated process.

Table 5.16 presents the cointegration results. The results show that the coefficient (β) is found to be positive and significant at the 1% level in all cases. The largest β coefficient is found to be 1.03984 in South Africa and the lowest is 0.97249 in the case of Japan. The constants (α) are positive in HK, Japan, and the US, and negative in the other cases. The R^2 statistics are high and

---

[11]See section 4.3.1 of chapter 4.

seen to be close to one in all the cases and ranges between 0.981347 in the case of South Africa and 0.999938 in the case of USA. This indicates a good model fit.

In the residual unit root tests, the first order integration is tested with a trend and second order integration is tested without a trend. Thus, the first order integration test is testing for trend stationarity and the second order integration test testing for stationarity around the mean. The first order integration test starts with the maximum 15 lags and then lags are reduced by 3 lags at a time. However, the second order integration test have maximum lags of 36 in the case of the US and 24 lags in Japan, Germany, South Africa, and UK. Results with the lowest number of lags and with no serial correlation are presented. Using the Engle-Granger method, all series involved indicate a long-run cointegrated relationship between cash prices and futures prices.

5.1.5.2 Phillips and Hansen Method.

As stated in section 4.3.2, the Phillips and Hansen (1990) tests are also applied to test for the cointegration relationship. The variables log of cash price and futures price are assumed to be I(1) processes. Such non-stationary variables might drift apart in the short-run but in the long-run they are constrained. The following relationship is estimated by means of the Fully-Modified OLS procedure proposed by Phillips and Hansen (1990):

$$S_t = \alpha + \beta F_t + \varepsilon_t.$$

Again, S_t is log of cash index and F_t is log of futures index and both variables are I(1). In this method, cointegration between the cash and futures variables are tested applying the Phillips and Hansen procedure where none of the regressors has a drift. The Parzen lag window as recommended is applied. After saving the residuals of the relationship, the unit root test (ADF) was applied to check for the stochastic structure of the error term of the regression. The first order integration is tested with trend and second order integration is tested without trend.

The cointegration coefficients (α and β) estimated by the Phillips and Hansen method are presented in Table 5.16. The t-ratio for the Phillips and Hansen test is significant and also relatively similar to the results of the Engle-Granger (1987) test, while the coefficients are also close in values to the Engle-Granger estimation. This confirms the inferences based on the Engle-Granger cointegration method. Thus, for all the series involved, the error term does not contain unit roots and therefore, cash price and futures price are cointegrated. Thus, stock index and stock index futures prices are found to have a long-run relationship. Since the error correction term is depicted to possess long memory, the cointegration relationship analysed may give a better understanding of the relationship between the cash and futures prices, as the error correction responds to shocks so that deviations from equilibrium are more persistent.

5.1.6 The Bivariate GARCH-X (1, 1) Results.

As stated in chapter 4, GARCH models provide a more flexible framework to capture various dynamic structures of conditional variance and allow simultaneous estimation of several parameters and hypotheses. The GARCH model was extended by linking it to the error-correction models (ECM) of cointegrated series (Lee, 1994). This new model is called the GARCH-X model[12]. Short-run deviations from a long-run cointegrated relationship are indicated by the error-correction term from the ECM. According to Lee (1994), if the error -correction term from the cointegrated relationship affects the conditional variance, then conditional heteroskedasticity may be modelled as a function of the lagged error-correction term, and if shocks to the system that propagate on the mean and variance change volatility, then it is reasonable to study the behaviour of the conditional variance as a function of short-run deviations. Thus, the GARCH-X model may be used to show the effect of the long-run cointegrated relationship on the optimal hedge ratio, which is the focal point of this study.

The test of cointegration between the cash and futures prices is the first step in the estimation of the GARCH-X model. Table 5.16, described earlier, shows the cointegration results. A significant cointegrated relationship was found between the cash and futures prices in all of the seven

[12] See section 4.5 of chapter 4.

markets used. Tables 5.17 and 5.18 present the GARCH-X results[13]. These results show that the ARCH parameters A_{11} and A_{33} are significant and less than one in all cash and futures tests, indicating the existence of volatility clustering in these markets. The ARCH coefficient in the residuals for the cash equation range between 0.0722 (US) and 0.156 (SA). The lowest ARCH coefficient in the futures equation is 0.08652 in the case of the Hong Kong and the highest is 0.127 in the case of the South Africa. The shocks to the conditional variance are not explosive since the ARCH coefficients (A_{11} and A_{33}) are less than unity. Meanwhile, the B_{11} and B_{33} coefficients are found to be positive in all cases and their significance expresses the existence of GARCH effects which indicates the impact of past variance. The covariance parameters (A_{22} and B_{22}) are all positive and significantly different from zero, implying strong interaction between the cash and futures prices in all cases. The persistence measure (A_{11} + B_{11}, A_{33} + B_{33}) in the GARCH-X results indicates a high level of persistence of shocks to volatility with German data showing the highest persistence of shocks to volatility, while the Australian data shows the lowest persistence. Tables 5.17 and 5.18 show significant MA terms (θ_1 and θ_2) in all cases, which may once again be due to non-synchronous trading. The parameters D_{11} and D_{33} measure the effects of the short-run deviations on the conditional variance of the cash and futures returns, respectively. The parameters D_{22} measure the effects of the short run deviation on the conditional covariance. Most parameters are found to be positive and significant, which implies that the stock prices become more volatile and harder to predict as the deviation between the cash and futures prices gets larger. The error correction parameters in the cases of Australia and Germany seem to have a significant negative effect indicating that an increase in the spread between the spot and futures prices reduces volatility.

The serial correlation in the standardised squared residuals for the order of 6 are presented in Table 5.19. The results show no serial correlation for the standardised squared residuals in most cases. However, the Australian cash series shows no serial correlation at 6 lags, but the futures series may contain serial correlation. Serial correlation exists for both US cash and futures returns, significant at less than the 1% level, but there is no serial correlation at the higher lag length.

---

[13]The GARCH-X is also estimated by means of the BHHH method. The specification is presented in section 4.5 of chapter 4.

5.1.6.1 Comparison of the Hedge Ratios.

This section provides a comparison of the time-varying hedge ratio method using the GARCH-X model to other methods such as the GARCH method and the constant hedge methods (i.e. unhedged, traditional, and the minimum variance). This comparison is carried out by constructing portfolios for every method as described in section 5.1.4.1, then comparing the variance of these constructed portfolios. The smaller the variance the more effective the hedge ratio.

Table 5.20 part A shows that the variances of portfolios using the GARCH-X model hedge ratio are smaller in value than the GARCH, unhedged, and traditional methods in most of the cases. However, in comparison to the minimum variance method, the GARCH-X variance is smaller only in the cases of Australia, Hong Kong and South Africa. Table 5.20 part B shows the percentage changes in the variance of portfolios estimated using the GARCH-X hedge ratio versus the other hedge ratios. The comparison is provided between GARCH-X hedge ratio portfolios and other hedge ratio portfolios only.

The GARCH-X hedge ratio is highly effective compared to the unhedged and traditional methods. The GARCH-X outperforms the traditional methods in most of the cases except in Japan where the difference in the variance is modest, while the GARCH-X outperforms the unhedged ratios in every case involved. The hedge ratios of the GARCH-X model are more effective than the standard GARCH in four cases, the exceptions being Germany, Hong Kong and South Africa where the differences are less than 1%. The reduction in the variance of the portfolio using the time-varying GARCH-X ratio is small in comparison to the GARCH portfolios for the cases of Australia, Japan, UK and US. The portfolios constructed from the time varying hedge ratio of the GARCH and GARCH-X models performs similarly overall. Comparing the time-varying hedge ratios the GARCH-X model tends to marginally outperform the GARCH model. Therefore, the short-run deviation of a long-run cointegrated relationship between cash and futures prices improves the time-varying hedge ratio marginally when linked to the GARCH model in these cases.

The GARCH-X outperforms the minimum variance hedge ratio for Australia, Hong Kong and

South Africa. The GARCH model also outperformed the minimum variance hedge ratio for the same three series. The percentage changes in variance in the GARCH-X compared to the minimum variance in both Australia and Hong Kong are marginally bigger than that of the GARCH cases. However, in the South Africa case the reduction of variance in the comparison between the GARCH and the minimum variance hedge ratio is slightly bigger than that of the GARCH-X. The US and Japan minimum variance hedge ratio provides the portfolios with the lowest variance compared to the time-varying hedge ratio, but the difference between the time-varying hedge ratio portfolio variance and the constant minimum variance hedge ratio is small for Germany and the UK.

It is noticeable that the GARCH-X provides the lowest variance portfolios compared to all other ratios in the case of Australia. While GARCH provides lowest variance portfolios in Hong Kong and South Africa marginally and the minimum variance provides the lowest variance in the cases of Germany, Japan, the UK and the US. The comparisons reveal that the dynamic hedging strategy based on the bivariate GARCH and GARCH-X estimation improve the hedging performance over the unhedged and the traditional hedging strategy while marginally improve the hedging performance in some cases in comparison to the minimum variance hedge methods. The risk minimising hedge ratio increases toward one as delivery date approaches. From the Tables 5.15 and 5.20 for the within-sample time period we notice that the reduction in variance varies in the different methods involved in our study.

The size of investment in the markets vary, as portfolio managers increase their investment by buying index futures and they decrease it by selling index futures accordingly. As stated earlier the transaction costs involved with the frequent reconstructing of the hedge portfolio for the time-varying optimal hedge ratio may be high. The GARCH-X reduces risk by less than 1% compared to the standard GARCH in cases of Japan, UK and the USA. The conventional minimum variance method reduces the risk by more than 6% and 11% in Japan and the USA, respectively, and marginally reduce the risk in Germany and the UK. for the other cases, the constant minimum variance method marginally outperforms the time-varying methods. Based on this with-in-sample testing, daily reconstructing of portfolios may not be worth undertaking. However, the GARCH-X method reduces the risk significantly in comparison to the unhedged and traditional strategy. This may motivate the investors to hedge using the minimum variance hedge ratio method, as the transaction costs limit the use of the time-varying methods. The small drop in variance advocates that the portfolio managers may opt for the constant minimum variance method instead of the standard GARCH or the GARCH-X model as the trade off between the risk reduction and transaction costs will determine the practicality of the time-varying hedging methods. More direct evidence is presented in chapter 7.

5.1.7 Different Patterns of Results Across Markets.

Figure 5.1 to 5.8 show the minimum variance constant hedge ratio and time-varying hedge ratio. The variation of time-varying hedge ratio propagate around the constant minimum variance hedge ratio in each case. The Figures indicate at periods large divergence between the time-varying and the constant hedge ratio. The time-varying hedge ratios are centred around 0.8483 and 0.9002 in the UK and the USA cases, respectively.

The variation of time-varying hedge ratios propagate around the constant minimum variance hedge ratio in each case. Although the bulk of the movement of the time-varying ratios is confined around the constant minimum variance hedge ratio, the figures indicate that at times there are large divergences between the time-varying and the constant hedge ratio. The hedge ratio is defined as the covariance between cash and futures returns divided by the variance of futures return. Therefore, if the numerator and the denominator in the hedge ratio formula are stable, then the hedge ratio is stable. However, any instability of the variance of futures returns with stable covariance between cash and futures returns creates variation in the hedge ratio. The same is true for stable variance of futures return with unstable covariance between cash and futures returns.

In the stock markets, the time-varying hedge ratios using the UK and US indices show movement which is restricted close to the constant minimum variance hedge ratios. Meanwhile, occasional large divergences between the time-varying and the constant minimum variance hedge ratio were demonstrated in the other cases. In most cases the widest variations were observed during the period of the Asian financial market crisis around 1997 and 1998. From the Table 5.21 for the stock markets in the GARCH method, in the cases of Australia, Germany, Hong Kong, Japan and South African, the highest hedge ratio was seen in Japan at 1.45793 and the lowest in Hong Kong at -0.01687. Meanwhile, from Table 5.22 for the GARCH-X method, the maximum value for the hedge ratio is 1.45899 again in Japan and the minimum value is -0.06494 in Australia. A negative hedge ratio indicates that it is wise to take a long position in futures. Based on variance and range, the most stable hedge ratio are observed in the UK, Australia, and the US for both GARCH and GARCHX models.

According to Gizycki and Lowe (2000) the reduction in financial risk in Australia during the 1990s is suggested by a number of factors such as a shift by banks into assets with relatively low credit risk, improved market scrutiny and discipline, greater diversification of profit sources, an improvement in internal risk-measurement and management methodologies and an improvement in financial system infrastructure. According to Directorate-General for Economic and Financial Affairs (2002), the economic growth in Germany has been lacklustre during the 1990s. This may be caused by the rigid labour market and unification-related problems. Meanwhile, the variation of time-varying hedge ratios in Germany may be caused by the unstability and uncertainty in the German economy during the decade of 1990s, which may have had an impact on the stock market. This impact results in variable futures return variance and from the hedge ratio definition, the hedge ratio gets more volatile.

According to Bank of Japan (1999) the apparent weakened recovery process of the Japanese economy in the early 1990s and up to 1993 is the stagnation of non-manufacturing industry. However, the period from 1994 to 1997 show a stark contrast to the early period of the 1990s as shown in the graph. The large variations during 1997 and 1998 in Hong Kong and Japan may be caused by the Asian financial crisis during the same period. The large variation of the time-varying hedge during the whole of the period involved for the case of South Africa may be the reflection of the major events the country went through during the decade of the 1990s. Such events are the ultimate demise of apartheid and the country's first all-race elections (South Africa, 1991).

However, the time-varying hedge ratios (GARCH) are centred around 0.84219 and 0.90437 in the UK and the USA cases, respectively. The stability for the UK and the US markets are indicated by the small variances from Table 5.21 (GARCH) and also indicated by the ranges of 1.01728 and 1.04117 for the GARCH model in both markets, respectively. Similar observation can be made for the GARCH-X case in Table 5.22. This may highlight the similarity between time-varying and minimum variance hedge ratios for both the UK and the USA markets. The reasons for that may be that the two markets are the largest, oldest, stable and the most established futures markets around. According to Sutcliffe (1997) the volume and value of trading are larger in the UK and USA index futures than other futures markets. The view is that exchange-traded futures contracts are more liquid for their use. This may result in small price drops and small price swings with less deviations in futures prices from the underlying index. The time-varying hedge ratios show less variation for within-sample time periods.

Park and Switzer (1995) show that the time-varying hedge ratios indicate considerable variation over time for the S&P 500 index futures. According to their data, the hedge ratio ranges from 0.926 to 1.234 for the S&P 500 index. Meanwhile, from Table 5.21, the S&P 500 time-varying hedge ratio in the US ranges between 0.00562 and 1.04679 for the GARCH model. From the Figures 5.2 and 5.3, there is similarity to Choudhry (1999) with large variations in the graphs for the cases of Australia, Hong Kong and Japan. Park and Switzer (1995) noted that the range for the MMI is 0.989 to 1.156 and for the T35 it is 0.710 to 0.998.

Table 5.2

Basic Statistics For (Within-Sample) Time Period

Country	Variance	Skewness	Kurtosis
Cash Returns			
Australia	0.000065	-0.28959[a]	5.235[a]
Germany	0.000142	-0.5985[a]	6.270[a]
Hong Kong	0.000302	0.0821[c]	10.937[a]
Japan	0.000199	0.2126[a]	2.781[a]
South Africa	0.000095	-1.274[a]	16.209[a]
UK	0.00008	0.0802	2.4238[a]
USA	0.000074	-0.3591[a]	6.3813[a]
Futures Returns			
Australia	0.000105	-0.01074	3.29483[a]
Germany	0.000156	-0.51654[a]	8.28513[a]
Hong Kong	0.000394	0.50432[a]	12.60841[a]
Japan	0.000198	0.11621[b]	2.06142[a]
South Africa	0.000175	-1.12207[a]	21.56466[a]
UK	0.000101	0.06009	1.86886[a]
USA	0.000084	-0.40301[a]	7.48352[a]

Notes:
a, b & c imply significance at 1%, 5% & 10% level, respectively.

Table 5.3
ADF Unit Root Tests For (Within-Sample) Time Period

Country	Trend- First Order Integration		No Trend - Second Order Integration	
	Cash Price	Futures Prices	Cash Return	Futures Return
Australia	-0.009242[b] (-3.4376)/{0}	-0.01456[a] (-4.24556)/{0}	-0.94010[a] (-45.6093)/{0}	-1.15743[a] (-26.1517)/{3}
Germany	-0.003207 (-1.814)/{15}	-0.002778 (-1.4847)/{9}	-0.952174[a] (-11.0773)/{15}	-1.13647[a] (-19.792)/{6}
Hong Kong	-0.004135 (-2.5501){3}	-0.004664 (-2.5092)/{6}	-0.94585[a] (-23.6754)/{3}	-1.13670[a] (-19.6860)/{6}
Japan	-0.005987 (-2.4679)/{3}	-0.006049 (-2.5008)/{6}	-1.04469[a] (-50.6399){0}	-1.07751[a] (-18.5226)/{6}
South Africa	-0.003710 (-2.932)/{15}	-0.004167 (-2.5111)/{12}	-0.638610[a] (-10.4064)/{15}	-0.932633[a] (-12.6639)/{12}
UK	-0.006168 (-2.5368)/{6}	-0.006712 (-2.4641)/{9}	-1.11224[a] (20.4432)/{6}	-1.23899[a] (-20.1982)/{6}
USA	-0.002399 (-1.4660)/{6}	-0.002584 (-1.4627)/{6}	-1.18218[a] (-20.6998)/{6}	-1.26877[a] (-20.8855)/{6}

Notes:
a, b, & c imply rejection of the null of unit roots at the 1%, 5% & 10% level, respectively.
t-tests are in the parenthesis ( )
Number of lags in brackets { }

Critical values:
No Trend - 10% (-2.57%), 5% (-2.86), 1% (-3.43).
Trend - 10% (-3.12), 5% (-3.41), 1% (-3.96).

Tables 5.4
KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	Australia Cash Price	Australia Futures Price	Australia Cash Return	Australia Futures Return
0	4.22161[a]	4.12186[a]	0.0501	0.03011
3	1.06825[a]	1.04869[a]	0.04779	0.03474
6	0.61678[a]	0.60721[a]	0.04975	0.03806
9	0.43607[a]	0.43025[a]	0.05183	0.04151
12	0.33871[a]	0.33478[a]	0.05179	0.04273
15	0.27792[a]	0.27511[a]	0.05044	0.04196

Notes:
a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.
Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 5.5

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	Germany Cash Price	Germany Futures Price	Germany Cash Return	Germany Futures Return
0	36.68788[a]	36.90967[a]	0.16519	0.14847
3	9.22374[a]	9.28357[a]	0.17026	0.16202
6	5.29418[a]	5.32945[a]	0.17336	0.16522
9	3.72157[a]	3.74694[a]	0.18159	0.176
12	2.87413[a]	2.89405[a]	0.18252	0.178
15	2.34421[a]	2.36067[a]	0.17917	0.17584

Table 5.6

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	HK Cash Price	HK Futures Price	HK Cash Return	HK Futures Return
0	33.56264[a]	33.16226[a]	0.14499	0.11684
3	8.43331[a]	8.34023[a]	0.13689	0.12782
6	4.84030[a]	4.78851[a]	0.13642	0.13154
9	3.40286[a]	3.36730[a]	0.13964	0.13719
12	2.62871[a]	2.60176[a]	0.1361	0.13499
15	2.14503[a]	2.12344[a]	0.13072	0.13017

Notes:
a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.

Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 5.7

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	Japan Cash Price	Japan Futures Price	Japan Cash Return	Japan Futures Return
0	8.93411[a]	9.00358[a]	0.06596	0.06599
3	2.25336[a]	2.27052[a]	0.0746	0.0736
6	1.29626[a]	1.30619[a]	0.07596	0.07489
9	0.91322	0.92025[a]	0.07703	0.0754
12	0.70693[b]	0.71244[b]	0.07611	0.0747
15	0.57806[b]	0.58261[b]	0.07592	0.07459

Table 5.8

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	SA Cash Price	SA Futures Price	SA Cash Return	SA Futures Return
0	38.76956[a]	41.01531[a]	0.23421	0.11315
3	9.72549[a]	10.30298[a]	0.17815	0.10884
6	5.577636[a]	5.91183[a]	0.16129	0.10984
9	3.91763[a]	4.15524[a]	0.15047	0.11194
12	3.02519[a]	3.20943[a]	0.1402	0.11048
15	2.46807[a]	2.61852[a]	0.13176	0.10709

Notes:

a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.

Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 5.9

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	UK Cash Price	UK Futures Price	UK Cash Return	UK Futures Return
0	30.47559[a]	31.89105[a]	0.04633	0.03837
3	7.69097[a]	8.06091[a]	0.0439	0.04071
6	4.42930[a]	4.64516[a]	0.04619	0.04417
9	3.12286[a]	3.27622[a]	0.04946	0.04861
12	2.41842[a]	2.53765[a]	0.0499	0.05002
15	1.97800[a]	2.07564[a]	0.04948	0.0503

Table 5.10

KPSS Unit Root Tests For (Within-Sample) Time Period

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	US Cash Price	US Futures Price	US Cash Return	US Futures Return
0	51.06831[a]	51.07131[a]	0.13633	0.11755
3	12.82398[a]	12.83040[a]	0.13836	0.13227
6	7.35376[a]	7.35829[a]	0.14854	0.14551
9	5.16392[a]	5.16741[a]	0.1616	0.16018
12	3.98374[a]	3.98657[a]	0.16651	0.16528
15	3.24573[a]	3.24815[a]	0.16805	0.16682

Notes:

a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.

Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 5.11

OLS Tests For (Within-Sample) Time Period

Countries	α	β	R^2	D.W.
Australia	0.000209[a] (2.6032)	0.6886[a] (87.9935)	0.7673	2.4345
Germany	0.000275[c] (1.9004)	0.7712[a] (66.404)	0.6525	2.7807
Hong Kong	0.000118 (0.7611)	0.7893[a] (100.922)	0.8127	2.6004
Japan	0.000079 (0.75506)	0.934[a] (124.074)	0.8677	2.6227
South Africa	0.000337[a] (3.1964)	0.6285[a] (78.6309)	0.7248	2.0684
UK	0.000164[a] (2.9537)	0.8483[a] (153.701)	0.9096	2.3724
USA	0.000192[a] (3.8123)	0.9002[a] (163.648)	0.9194	2.6148

Notes:

t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%

Table 5.12
BGARCH Results For (Within-Sample) Time Period

Parameters	Australia	Germany	Hong Kong
α_1	0.00047[a] (3.2995)	0.00078[a] (4.6161)	0.00127[a] (5.0492)
θ_1	0.0918[a] (5.7917)	0.2002[a] (11.3591)	0.079[a] (5.1177)
α_2	0.00035[a] (2.2078)	0.00064[a] (4.0317)	0.00122[a] (4.9626)
θ_2	0.2223[a] (14.1947)	0.3325[a] (19.3649)	0.2086[a] (13.4209)
C_1	0.0000062[a] (12.1598)	0.0000057[a] (9.9651)	0.000012[a] (17.5746)
A_{11}	0.0727[a] (15.2832)	0.0848[a] (12.7556)	0.1216[a] (20.5651)
B_{11}	0.8296[a] (86.6107)	0.8764[a] (100.894)	0.8335[a] (137.343)
C_2	0.0000087[a] (12.299)	0.0000068[a] (13.2936)	0.000012[a] (14.8217)
A_{22}	0.0735[a] (13.0513)	0.0753[a] (13.2187)	0.1008[a] (20.5366)
B_{22}	0.8066[a] (69.6246)	0.8734[a] (114.657)	0.8547[a] (154.984)
C_3	0.0000142[a] (10.2691)	0.0000104[a] (15.5864)	0.000012[a] (11.7365)
A_{33}	0.0785[a] (10.7563)	0.0871[a] (12.4196)	0.0914[a] (20.3774)
B_{33}	0.7838[a] (47.8452)	0.8509[a] (96.8027)	0.8721[a] (161.815)
L	21739.26	20223.64	19290.4

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.13
BGARCH Results For (Within-Sample) Time Period

Parameters	Japan	South Africa	UK	US
α_1	0.00028 (1.5347)	0.000809[a] (5.0604)	0.00062[a] (4.4696)	0.000708[a] (6.0821)
θ_1	0.22439[a] (14.5819)	-0.08048[a] (-4.0802)	0.1169[a] (6.7158)	0.209[a] (12.2658)
α_2	0.00018 (0.99142)	0.000396[a] (2.0433)	0.000496[a] (3.5022)	0.000596[a] (5.1908)
θ_2	0.24931[a] (16.5109)	0.07464[a] (4.01531)	0.1917[a] (11.5982)	0.2566[a] (15.2506)
C_1	0.0000163[a] (11.9998)	0.0000067[a] (16.048)	0.0000109[a] (10.9814)	0.0000041[a] (12.1663)
A_{11}	0.11853[a] (14.336)	0.169[a] (18.96602)	0.1176[a] (19.5607)	0.075[a] (18.7029)
B_{11}	0.8039[a] (70.5041)	0.744[a] (67.3176)	0.736[a] (53.8977)	0.8592[a] (127.793)
C_2	0.0000151[a] (10.8358)	0.0000072[a] (15.956)	0.000011[a] (11.103)	0.0000047[a] (12.5045)
A_{22}	0.10361[a] (12.9488)	0.146[a] (19.4698)	0.1098[a] (17.2575)	0.0795[a] (18.7542)
B_{22}	0.81717[a] (68.005)	0.763[a] (76.9992)	0.7472[a] (56.804)	0.847[a] (123.498)
C_3	0.000015[a] (9.7543)	0.0000127[a] (15.3873)	0.000012[a] (10.9692)	0.0000052[a] (12.3917)
A_{33}	0.103452[a] (12.6165)	0.146[a] (20.6862)	0.1071[a] (14.4741)	0.0886[a] (17.0733)
B_{33}	0.82035[a] (64.4369)	0.763[a] (68.5152)	0.7667[a] (58.8858)	0.8384[a] (114.131)
L	20542.2	20875.59	22701.45	23409.68

Notes:
a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood.

Table 5.14

Test for Higher Order Arch Effect (GARCH Model)

Series	Ljung-Box	Australia	Germany	Hong Kong	Japan	South Africa	UK	US
Cash Equations								
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	9.0252[b]	0.5351	1.5741	1.9795	4.4009	6.3855	11.2547[b]
Futures Equations								
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	8.8762[b]	0.161	2.6755	2.9565	3.4452	6.1508	11.7098[a]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals
a and b imply significance at 1% and 5%, respectively.

Table 5.15

The Standard GARCH Method Versus Conventional Methods
With-in-Sample Time Period (1st January 1991- 31st December 1999) GARCH Results

part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	0.0000651	0.000142	0.000302	0.000199	0.0000953	0.0000801	0.0000741
Traditional	0.0000253	0.0000575	0.000074	0.0000271	0.0000503	0.0000095	0.0000068
Minimum Var	0.0000151	0.0000493	0.000056	0.0000263	0.0000262	0.0000072	0.0000059
BGARCH	0.0000147	0.0000501	0.000055	0.0000279	0.0000256	0.0000073	0.0000066

Part B

Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	77.41	64.71	81.78	85.97	73.13	90.88	91.09
Traditional	41.89	12.86	25.67	-2.95	49.10	23.15	2.94
Minimum Var	2.64	-1.62	1.78	-6.08	2.29	-1.38	-11.86

Table 5.16
Cointegration Tests For (Within-Sample) Time Period

Country	Method	α	β	Method	Unit Root Tests	
					Trend	No Trend
					First Order Integration	Second Order Integration
Australia	E-G P-H	-0.0116* (-2.286) -0.0128* (-2.683)	1.0007* (1506.4) 1.0010* (1607.4)	E-G P-H	-0.116[a](-7.396)/{9} -0.117[a] (-7.398)/{9}	-2.866[a](-14.814)/{15} -2.865[a] (-14.812)/{15}
Germany	E-G P-H	-0.0471* (-18.286) -0.0488* (-20.770)	1.0049* (3074.9) 1.0052* (3370.6)	E-G P-H	-0.273[a] (-9.219)/{12} -0.272[a] (-9.194)/{12}	-5.308[a] (-13.044)/{24} -5.306[a] (-13.044)/{24}
HK	E-G P-H	0.0052 (1.172) 0.0048 (1.132)	0.9992* (2030.2) 0.9993* (2148.4)	E-G P-H	-0.153[a] (-8.154)/{6} -0.153[a] (-8.152)/{6}	-3.535[a] (-21.962)/{9} -3.534[a] (-21.962)/{9}
Japan	E-G P-H	0.2671* (34.735) 0.2665* (34.698)	0.9724* (1244.7) 0.9726* (1246.6)	E-G P-H	-0.179[a] (-8.604)/{6} -0.179[a] (-8.610)/{6}	-3.900[a](-18.317)/{12} -3.900[a] (-18.318)/{12}
SA	E-G P-H	-0.3201* (-12.444) -0.3223* (-12.714)	1.0398* (351.4) 1.0401* (356.9)	E-G P-H	-0.018[a] (-4.135)/{3} -0.018[a] (-4.135)/{3}	-1.339[a](-20.866)/{6} -1.339[a] (-20.867)/{6}
UK	E-G P-H	-0.0441* (-14.555) -0.0450* (-15.293)	1.0045* (2721.7) 1.0047* (2809.8)	E-G P-H	-0.074[a] (-6.208)/{12} -0.074[a] (-6.204)/{12}	-2.877[a](-12.490)/{24} -2.877[a] (-12.491)/{24}
US	E-G P-H	0.0248* (23.707) 0.0245* (24.268)	0.9954* (6141.6) 0.9955* (6367.3)	E-G P-H	-0.150[a] (-8.785)/{6} -0.150[a] (-8.785)/{6}	-4.205[a](-12.093)/{33} -4.205[a] (-12.093)/{33}

Notes:
***, **, * imply significance at 10%, 5%, and 1% respectively
a, b & c imply rejection of the null of unit root at 1%, 5%, & 10% level, respectively.
t-tests in the parenthesis ( )
Number of lags in brackets { }

Critical values:
No Trend 10% (-2.5672), 5% (-2.8633), 1% (-3.4362).
Trend 10% (-3.1289), 5% (-3.4143), 1% (-3.9674).
E-G denotes the Engle-Granger method
P-H denotes the Phillips and Hansen method

Table 5.17
BGARCH-X Results For (Within-Sample) Time Period

Parameters	Australia	Germany	Hong Kong
α_1	0.000433[a] (3.0033)	0.000767[a] (4.5507)	0.00118[a] (4.6373)
θ_1	0.08243[a] (4.6149)	0.198[a] (11.1908)	0.083666[a] (5.1916)
α_2	0.000308[a] (1.9089)	0.00062[a] (3.9646)	0.00113[a] (4.6197)
θ_2	0.208[a] (12.3239)	0.329[a] (19.1189)	0.20888[a] (13.2154)
C_1	0.000035[a] (9.8964)	0.0000057[a] (9.4846)	0.0000131[a] (12.4029)
A_{11}	0.133[a] (12.0632)	0.08436[a] (13.1773)	0.11755[a] (18.2816)
B_{11}	0.338[a] (5.9222)	0.883[a] (110.692)	0.81305[a] (130.868)
C_2	0.000036[a] (10.2206)	0.0000072[a] (13.3381)	0.0000124[a] (11.287)
A_{22}	0.115[a] (11.1268)	0.07556[a] (13.4528)	0.09633[a] (17.8946)
B_{22}	0.413[a] (8.4809)	0.88[a] (123.9207)	0.8401[a] (129.611)
C_3	0.0000409[a] (10.3821)	0.0000109[a] (16.6575)	0.0000124[a] (9.6805)
A_{33}	0.104[a] (9.4522)	0.08688[a] (13.2556)	0.08652[a] (17.5875)
B_{33}	0.508[a] (12.4878)	0.86[a] (110.467)	0.86241[a] (128.769)
D_{11}	-0.02907[a] (-28.4356)	-0.01596[c] (-2.3785)	0.07093[a] (7.5152)
D_{22}	-0.006758[c] (-0.77587)	-0.04172[a] (-6.2931)	0.04468[a] (4.2642)
D_{33}	-0.03171[b] (-7.60316)	-0.02701[a] (-4.2571)	0.05094[a] (5.2157)
L	21650.52	2230.98	19318.12

Table 5.18
BGARCH-X Results For (Within-Sample) Time Period

Parameters	Japan	South Africa	UK	USA
α_1	0.000254 (1.4104)	0.000768[a] (4.5150)	0.000604[a] (4.2247)	0.000692[a] (5.7988)
θ_1	0.22391[a] (14.3988)	-0.08064[a] (-4.4132)	0.11825[a] (6.6686)	0.2077[a] (12.1928)
α_2	0.000143 (0.78561)	0.00044[a] (2.2524)	0.000473[a] (3.2315)	0.000574[a] (4.8466)
θ_2	0.248404[a] (16.235)	0.07103[a] (3.7344)	0.19282[a] (11.4709)	0.2547[a] (14.9977)
C_1	0.000018[a] (11.1661)	0.0000062[a] (13.8549)	0.0000103[a] (10.0571)	0.0000038[a] (11.4308)
A_{11}	0.12634[a] (113.165)	0.156[a] (16.8999)	0.11817[a] (20.0733)	0.0722[a] (18.6003)
B_{11}	0.76469[a] (53.4028)	0.749[a] (67.8258)	0.7257[a] (48.4940)	0.8615[a] (133.527)
C_2	0.000017[a] (10.1769)	0.0000061[a] (15.3678)	0.0000109[a] (10.2543)	0.0000045[a] (11.6371)
A_{22}	0.10864[a] (12.0735)	0.130[a] (17.5500)	0.11081[a] (17.6087)	0.0776[a] (18.3026)
B_{22}	0.78314[a] (51.4732)	0.779[a] (82.9508)	0.73821[a] (51.0538)	0.8447[a] (119.769)
C_3	0.000017[a] (9.2848)	0.0000094[a] (13.1694)	0.0000115[a] (10.1770)	0.0000052[a] (11.5824)
A_{33}	0.10647[a] (11.9322)	0.127[a] (19.5418)	0.10794[a] (14.6609)	0.0882[a] (16.6393)
B_{33}	0.79344[a] (50.9912)	0.788[a] (72.7519)	0.75835[a] (53.5671)	0.8301[a] (107.005)
D_{11}	0.13113[a] (4.0244)	0.000577[a] (4.0149)	0.04570[a] (3.0832)	0.0277 (1.4188)
D_{22}	0.058101[b] (2.17409)	0.001529[a] (6.5171)	0.04165[b] (2.7723)	0.0719[a] (2.6913)
D_{33}	0.08033[a] (2.80371)	0.000589[a] (3.4279)	0.04161[b] (2.8375)	0.0460[a] (2.0580)
L	20558.71	20905	22712.35	23414.55

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.19

Test for Higher Order Arch Effect (GARCH-X)

Series	Ljung-Box	Australia	Germany	Hong Kong	Japan	South Africa	UK	US
Cash Equations								
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	6.7317	0.5922	1.9423	2.4788	4.7339	7.3988	11.6615[a]
Futures Equations								
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	8.1363[b]	0.2123	3.7321	3.2418	4.8159	6.8386	12.2464[a]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals
a and b imply significance at 1% and 5%, respectively.

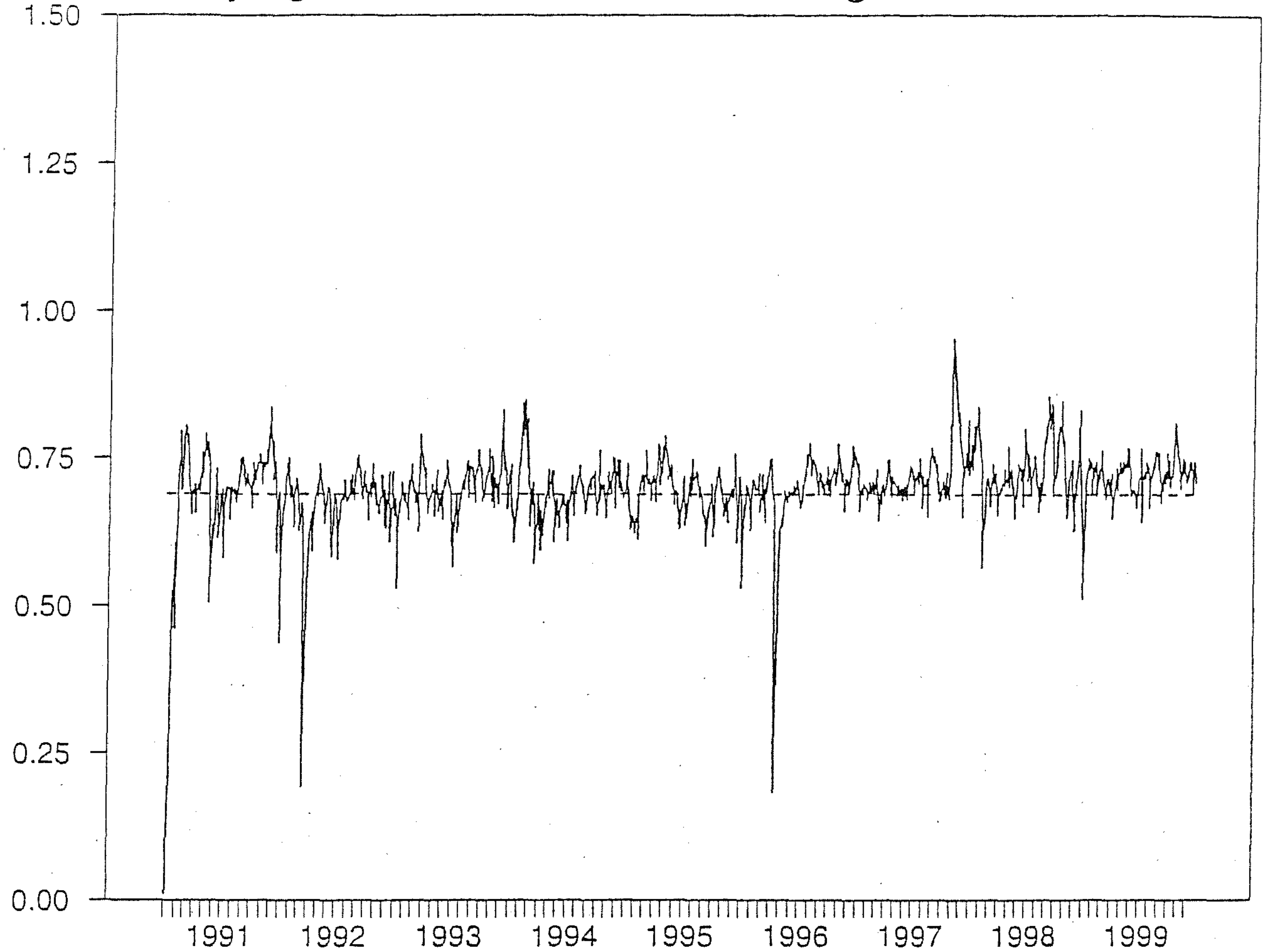
Table 5.20
The GARCH-X Method Versus The Standard GARCH and the Conventional Methods
Within-Sample (1st January 1991- 31st December 1999) Results
part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	0.0000651	0.000142	0.000302	0.000199	0.00009532	0.00008013	0.00007410
Traditional	0.0000253	0.00005756	0.00007409	0.00002715	0.00005036	0.00000956	0.00000680
Minimum Var	0.0000151	0.00004939	0.00005663	0.00002630	0.00002623	0.00000724	0.00000596
BGARCH	0.0000147	0.00005013	0.00005512	0.00002797	0.00002565	0.00000737	0.00000665
BGARCH-X	0.0000144	0.00005022	0.00005556	0.00002790	0.00002574	0.00000733	0.00000662

Part B
Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	77.88	64.63	81.60	85.97	72.99	90.08	91.06
Traditional	43.08	12.75	25.00	-2.76	48.88	23.32	2.64
Minimum Var	4.63	-1.68	1.88	-6.08	1.86	-1.24	-11.07
Bi-GARCH	2.04	-0.17	-0.79	0.25	-0.35	0.54	0.45

Time-Varying GARCH and Constant Hedge Ratios - Australia



Time-Varying GARCH and Constant Hedge Ratios - Germany

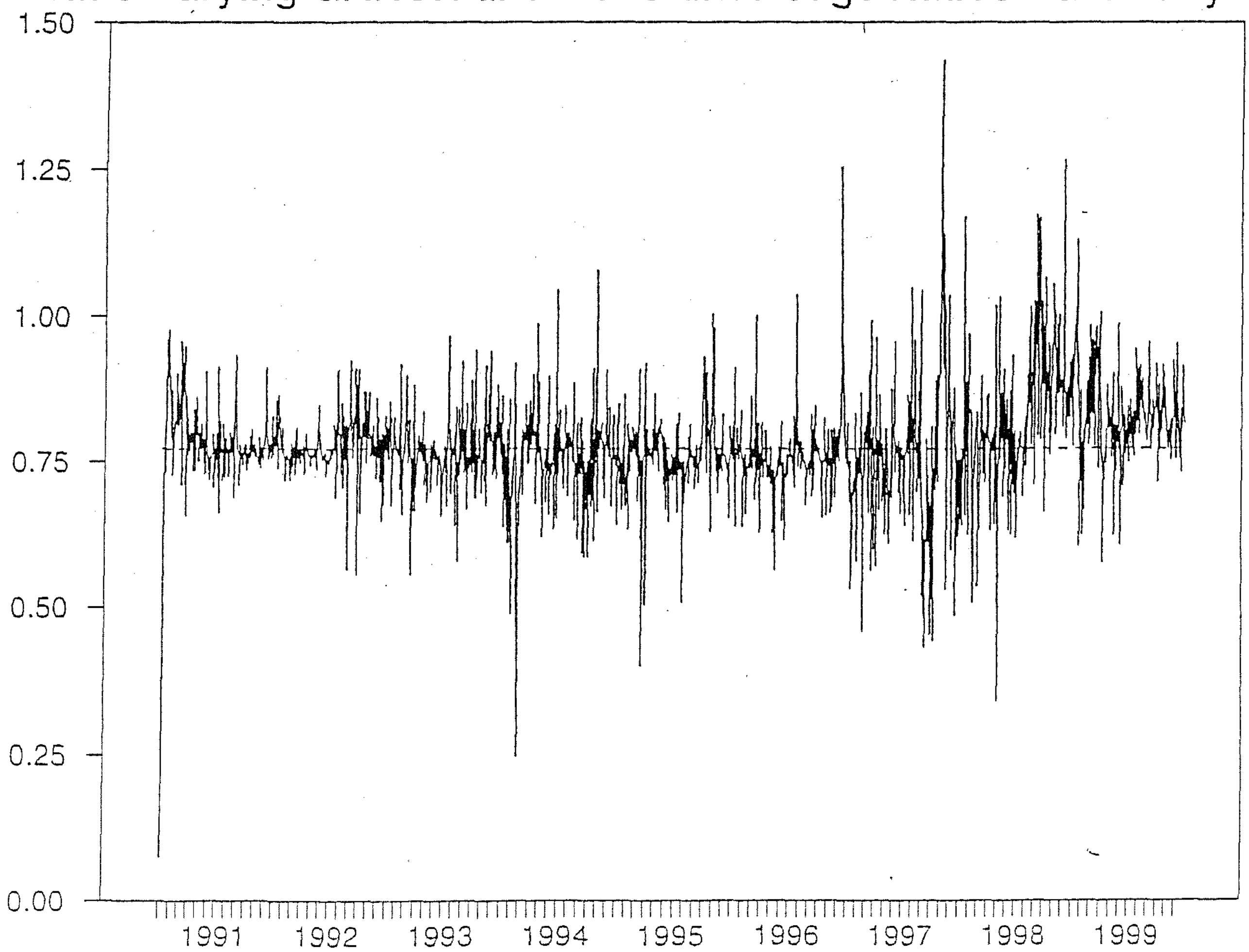
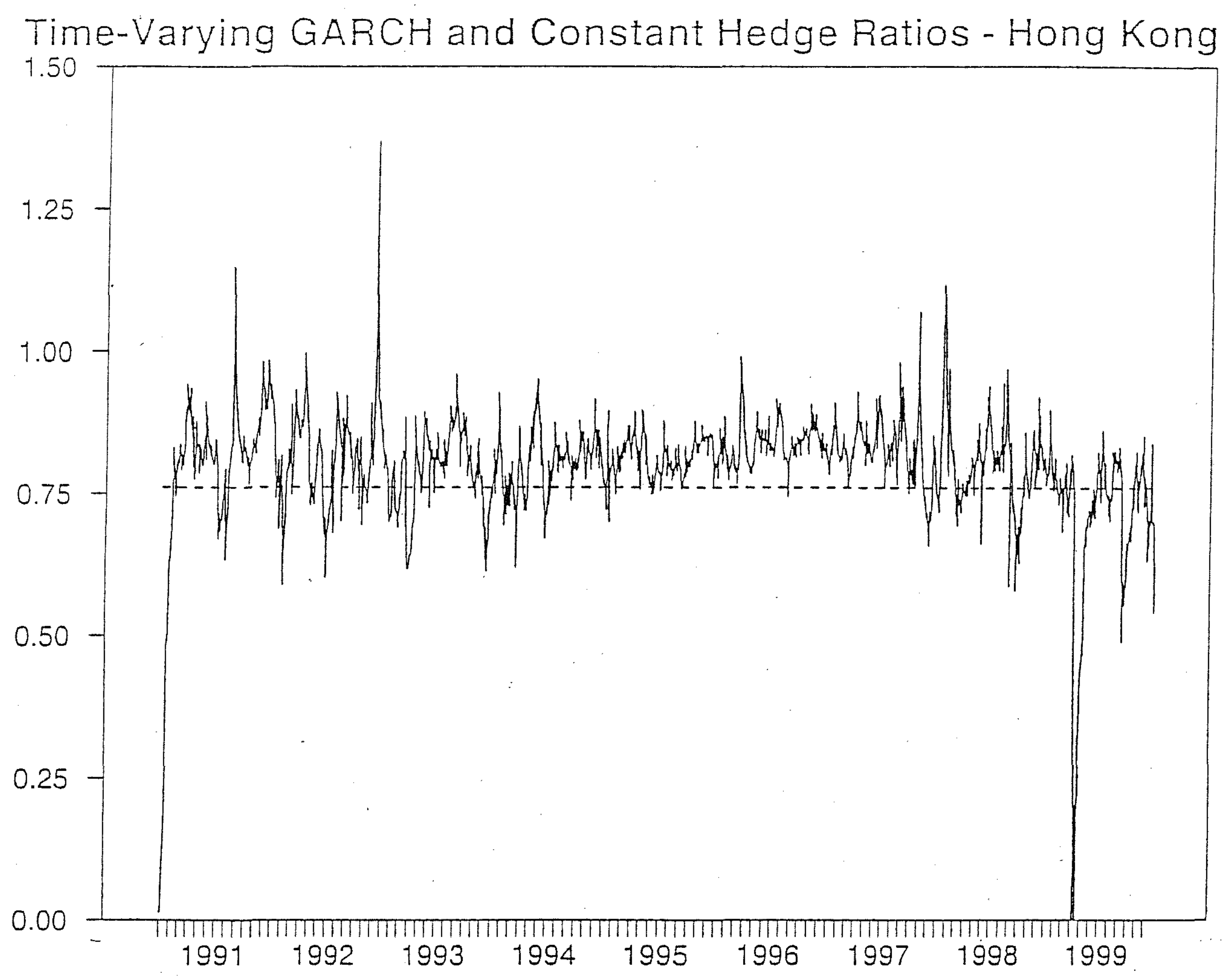
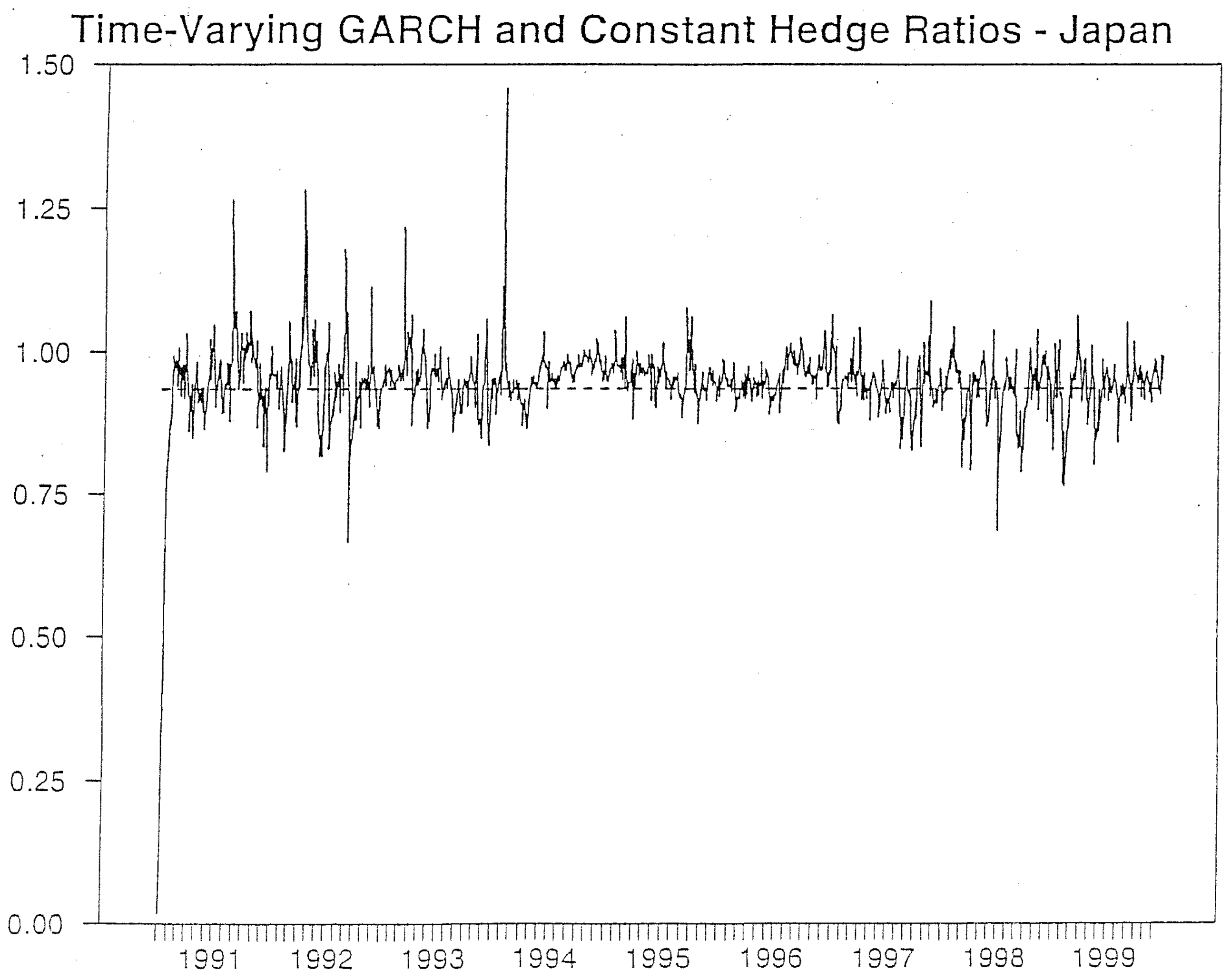


Figure 5.1

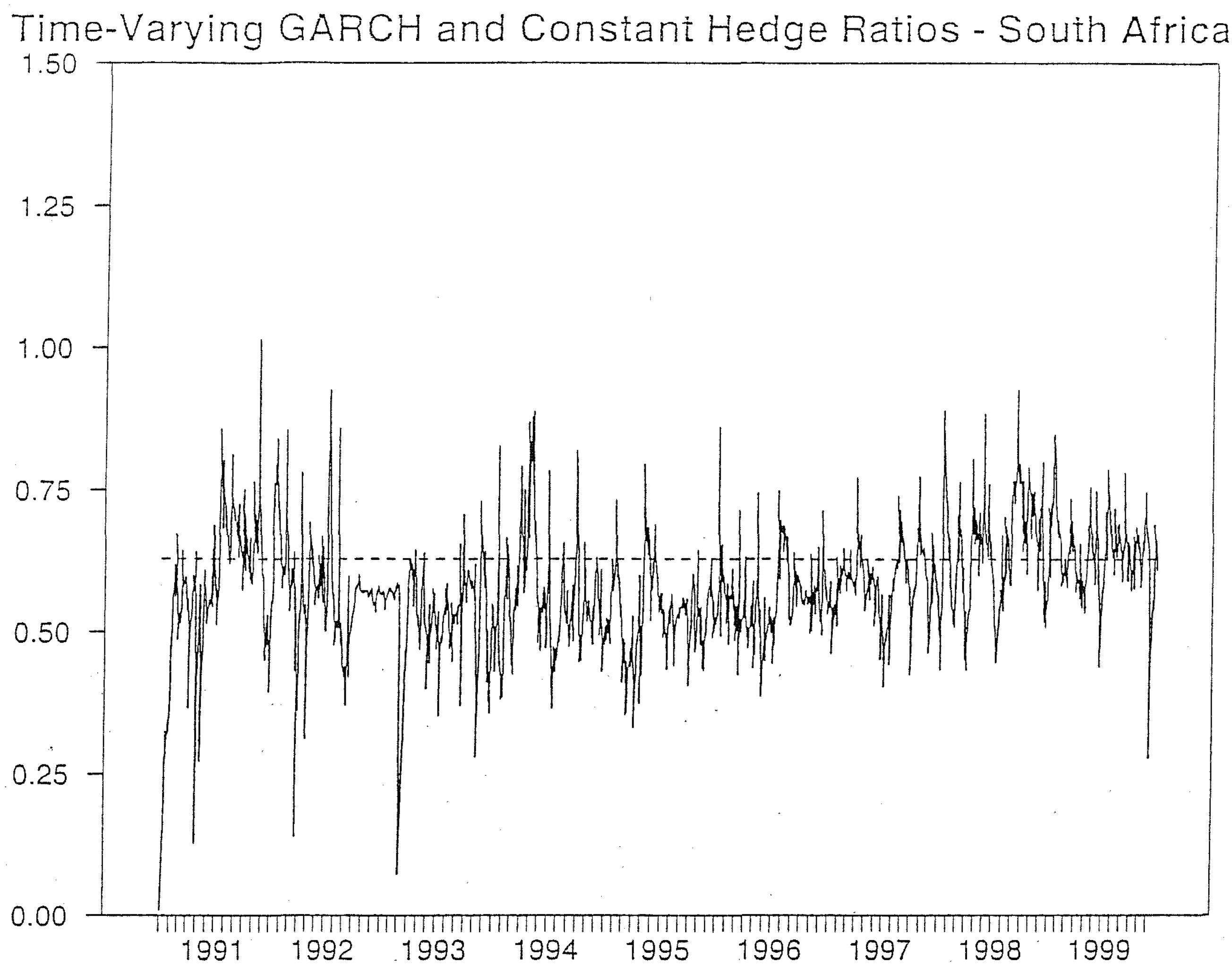


Time-Varying GARCH and Constant Hedge Ratios - Hong Kong
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999



Time-Varying GARCH and Constant Hedge Ratios - Japan
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

Figure 5.2


Time-Varying GARCH and Constant Hedge Ratios - South Africa
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

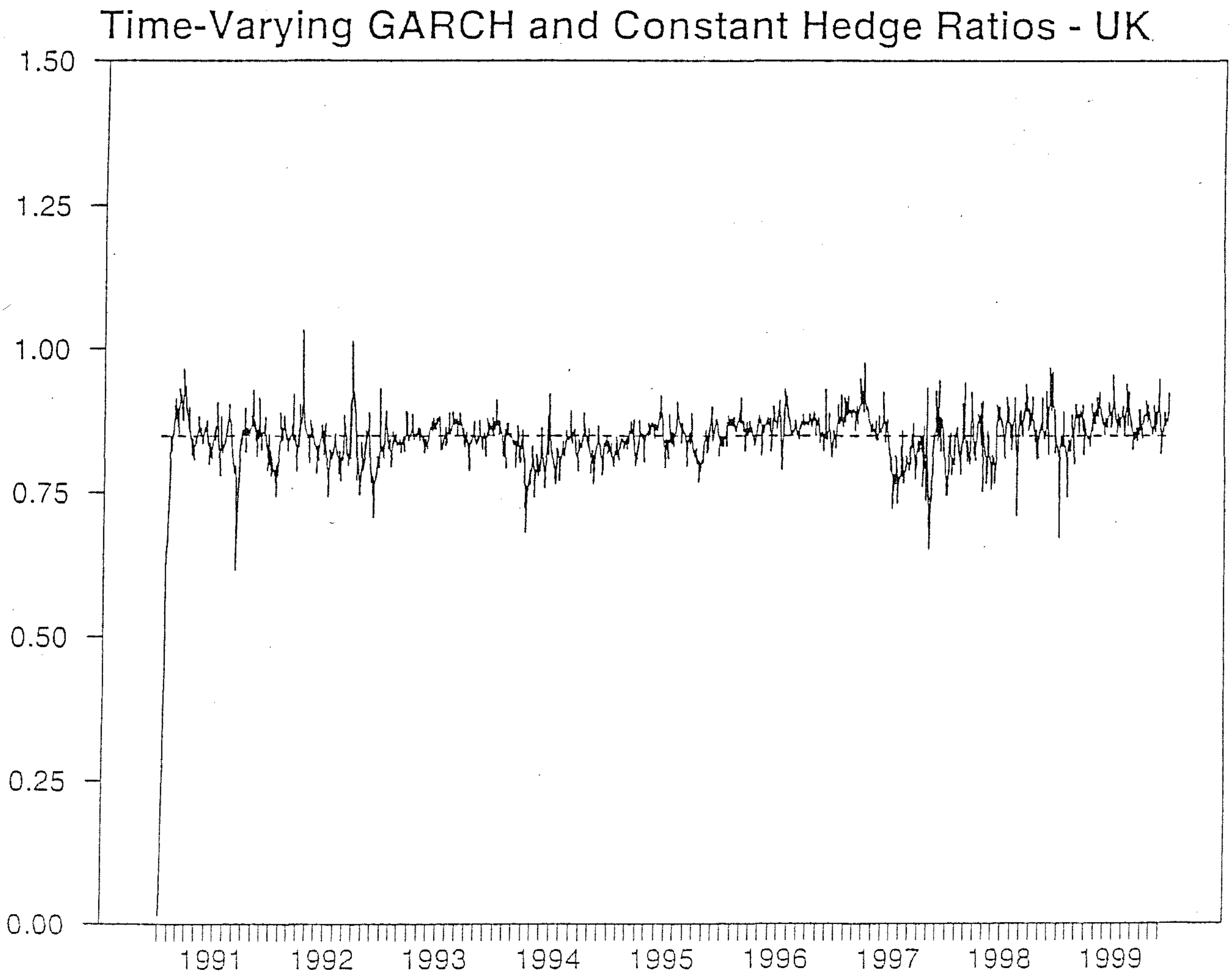

Time-Varying GARCH and Constant Hedge Ratios - UK
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

Figure 5.3

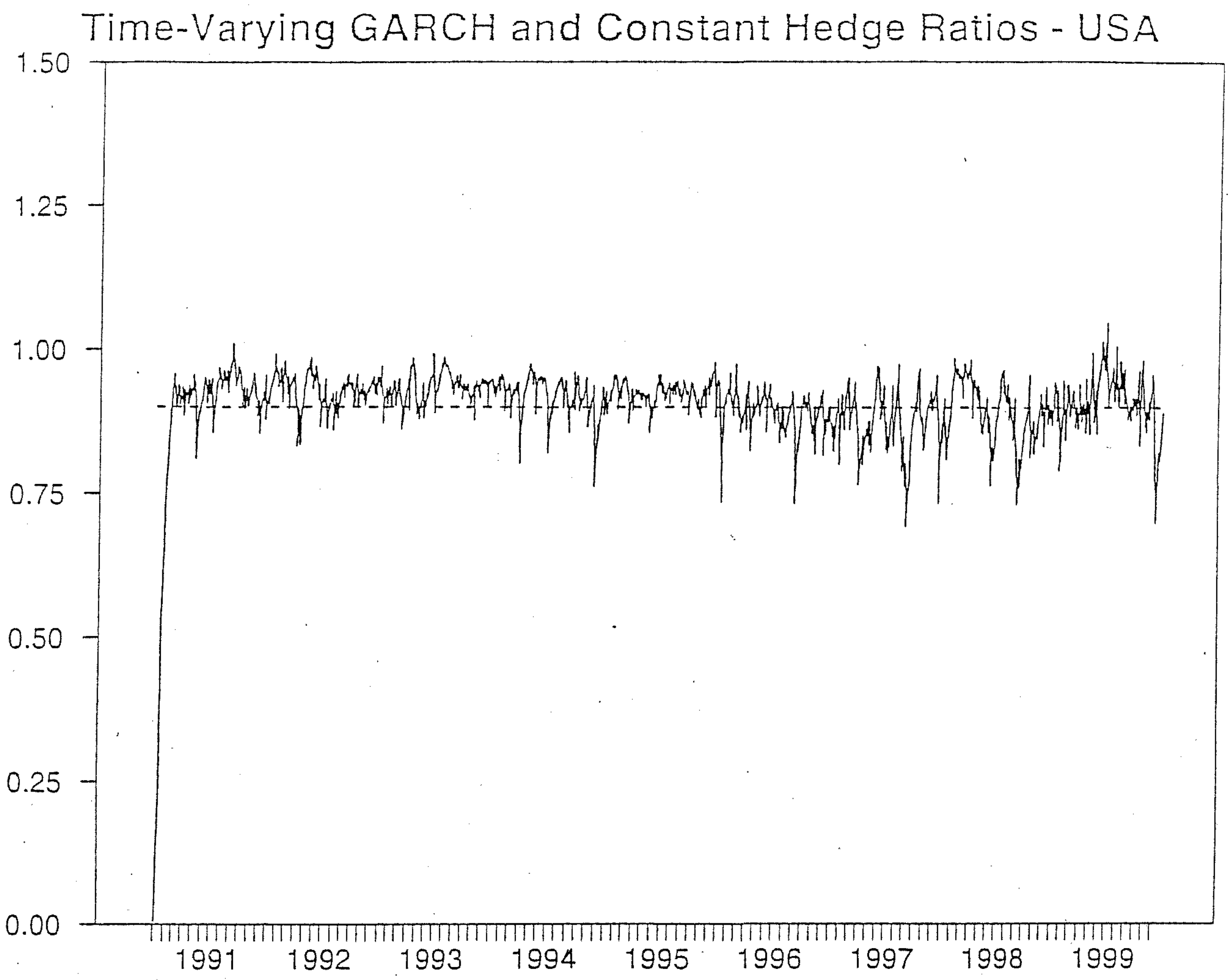
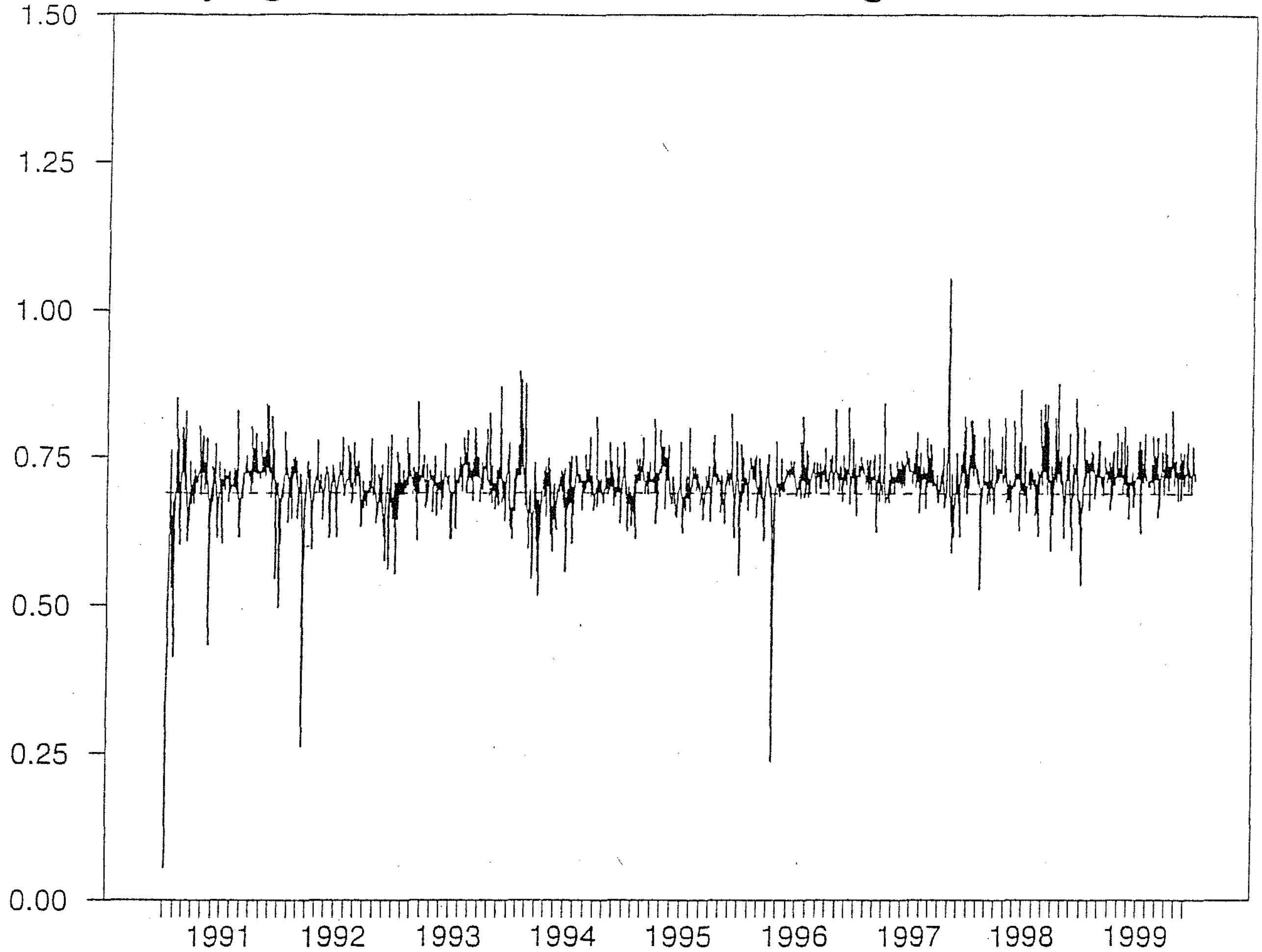

Time-Varying GARCH and Constant Hedge Ratios - USA
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

Figure 5.4

Time-Varying GARCH-X and Constant Hedge Ratios - Australia



Time-Varying GARCH-X and Constant Hedge Ratios - Germany

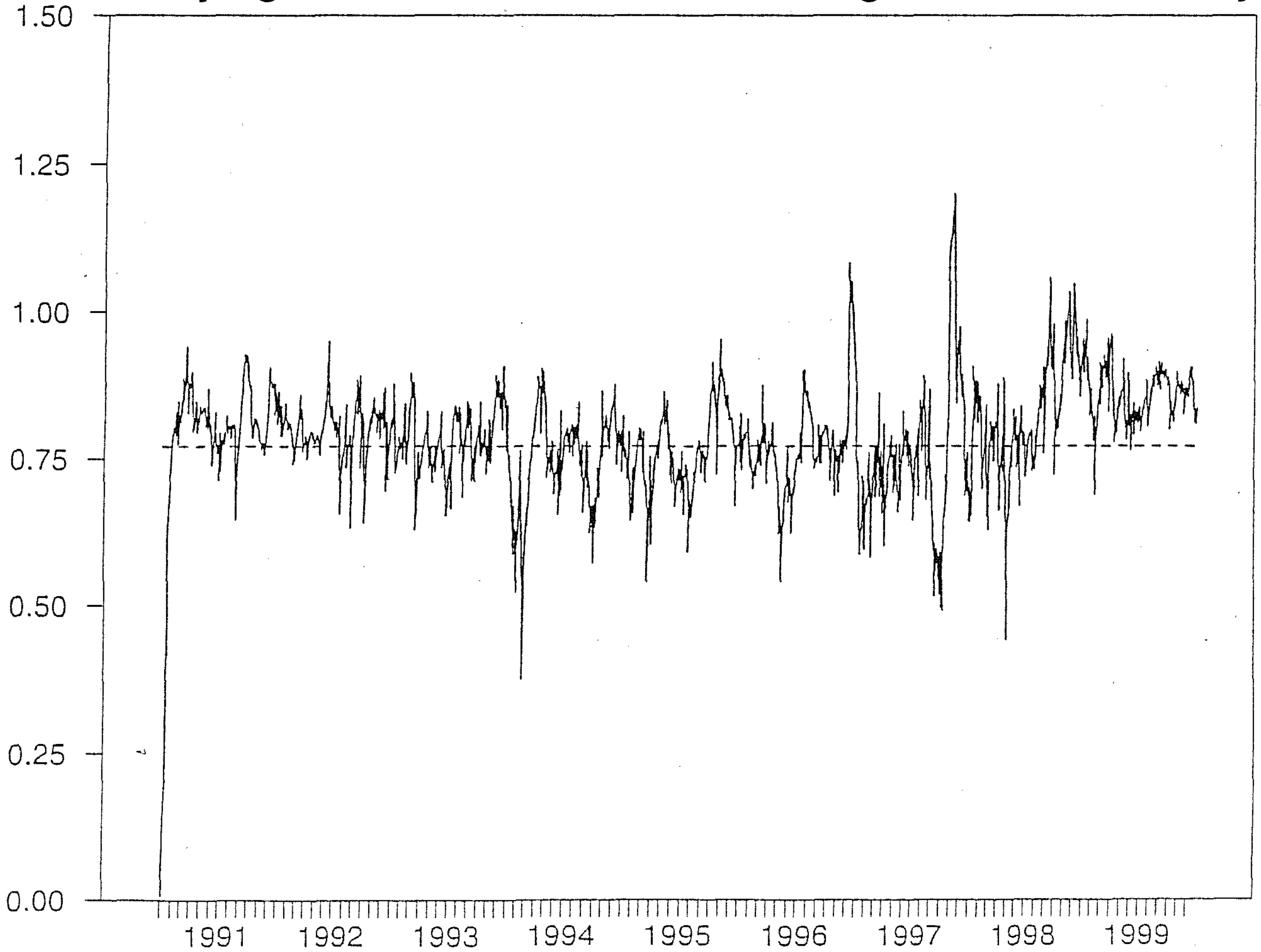
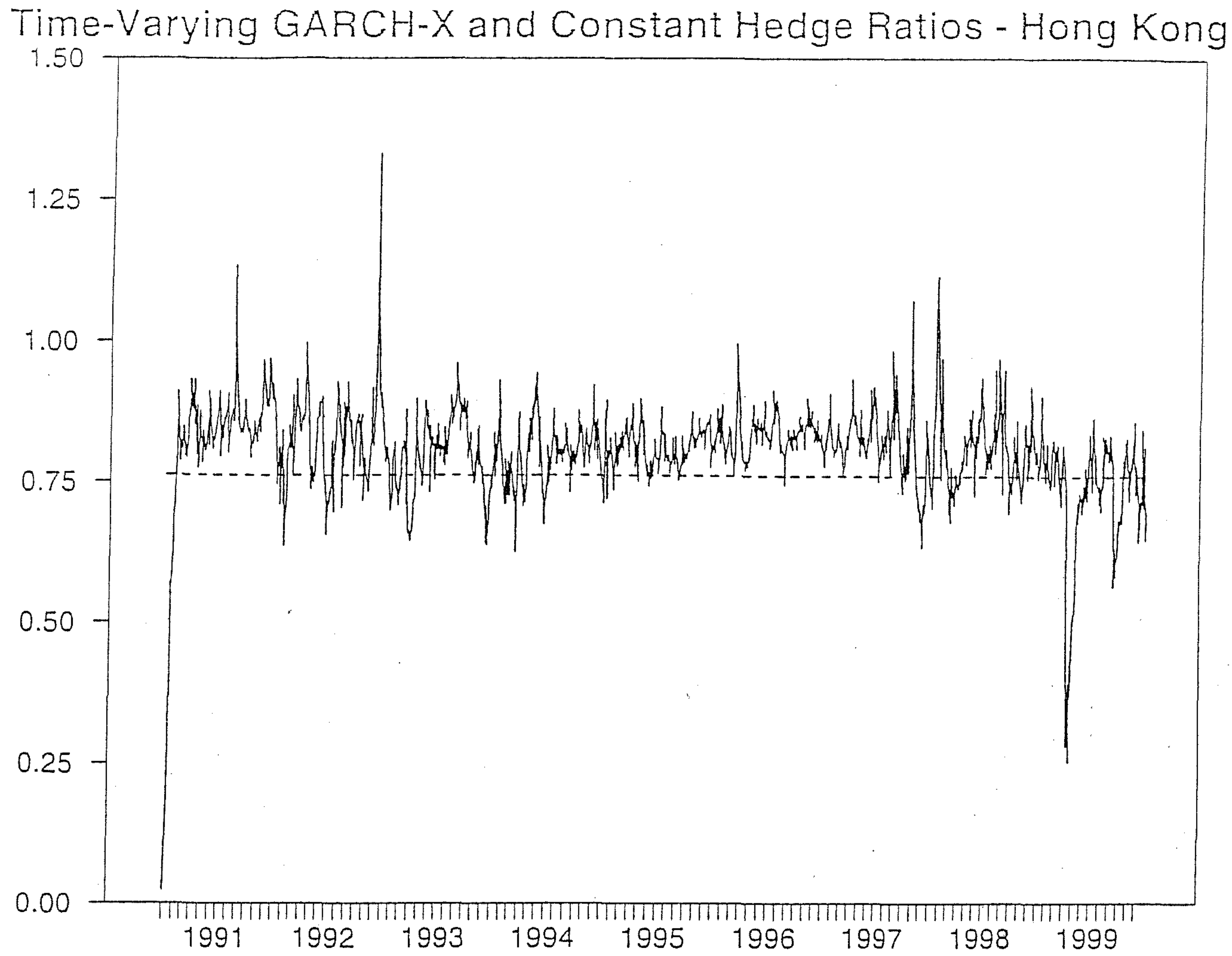
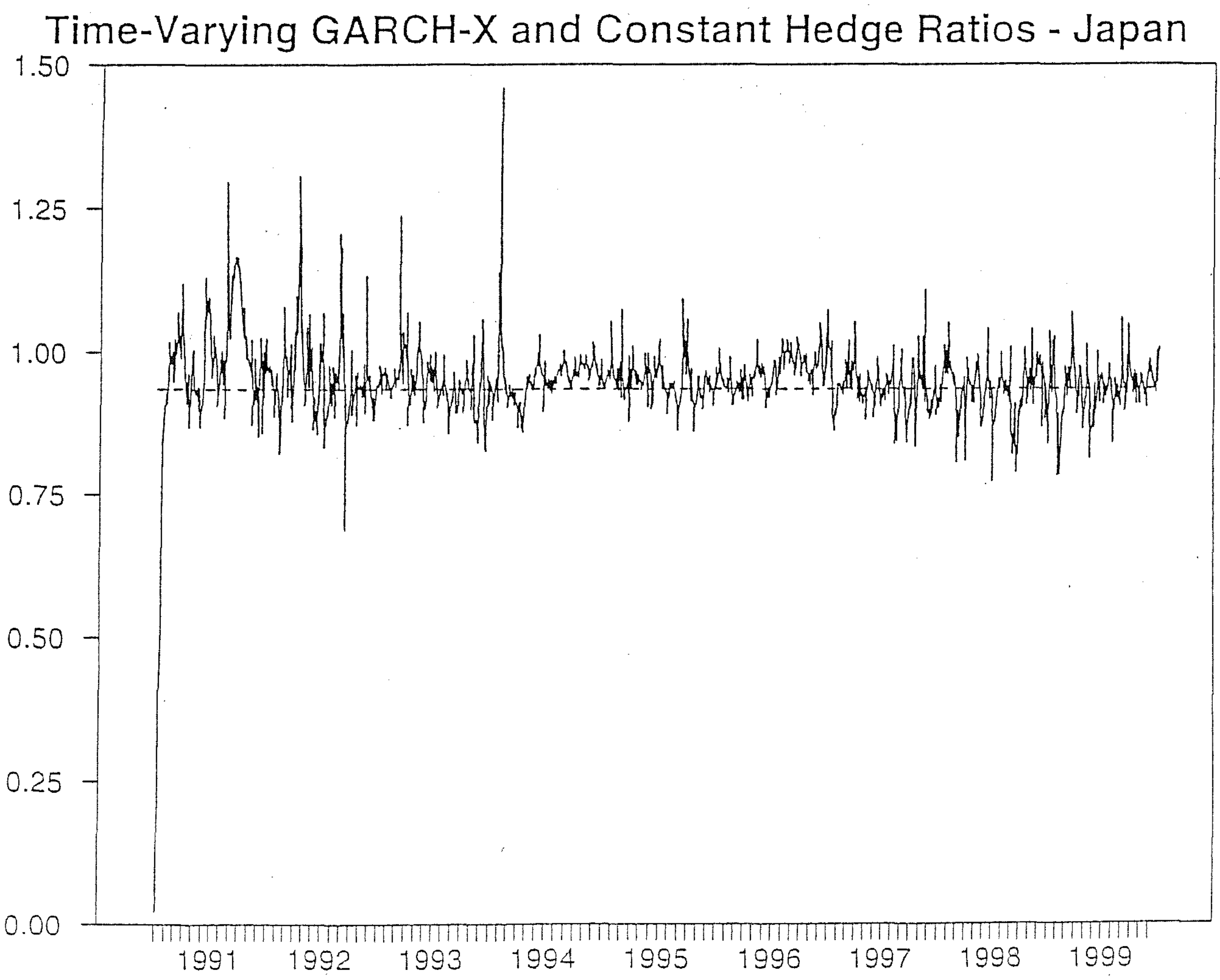


Figure 5.5



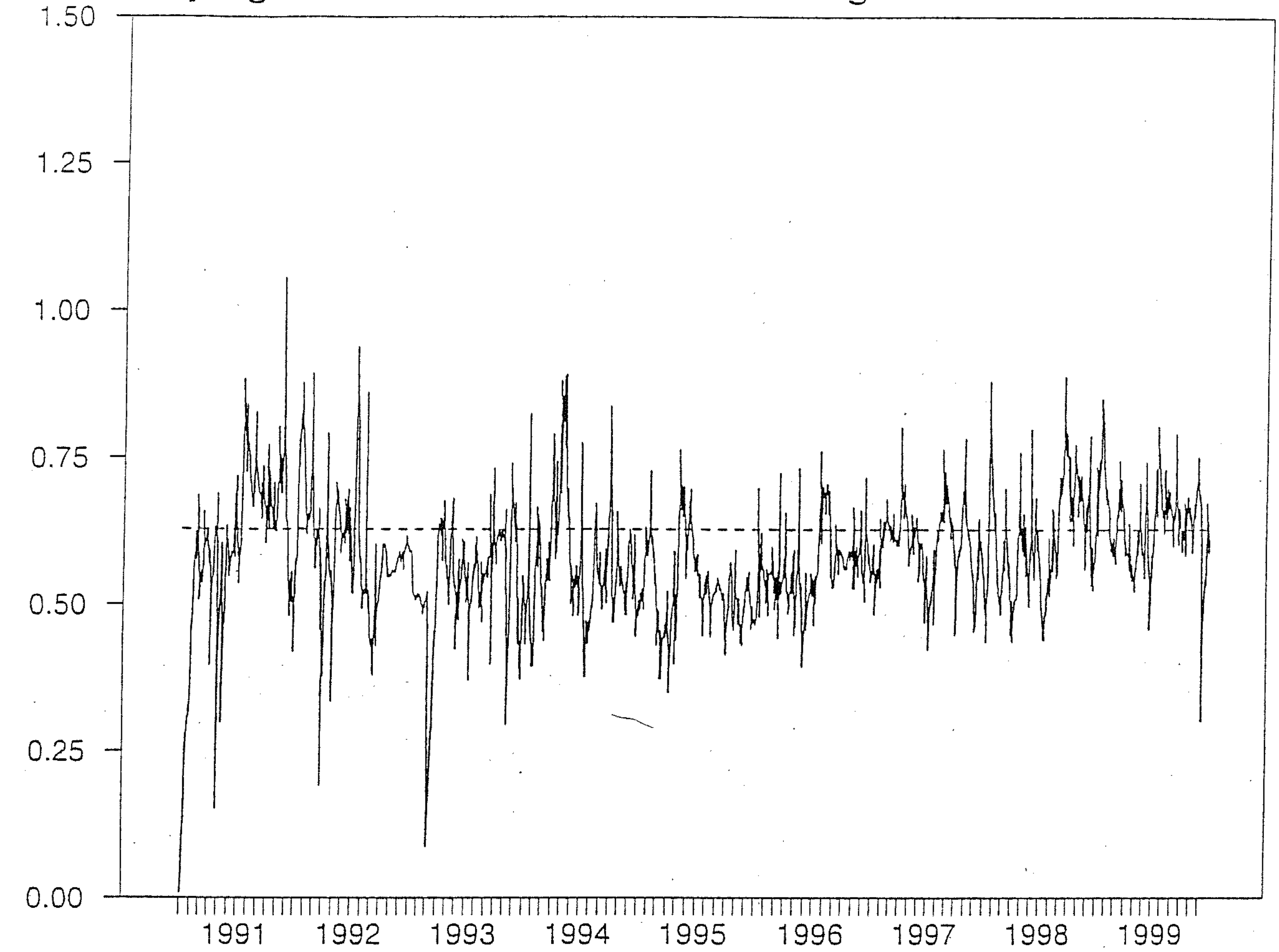
Time-Varying GARCH-X and Constant Hedge Ratios - Hong Kong
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999



Time-Varying GARCH-X and Constant Hedge Ratios - Japan
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

Figure 5.6

Time-Varying GARCH-X and Constant Hedge Ratios - South Africa



Time-Varying GARCH-X and Constant Hedge Ratios - UK

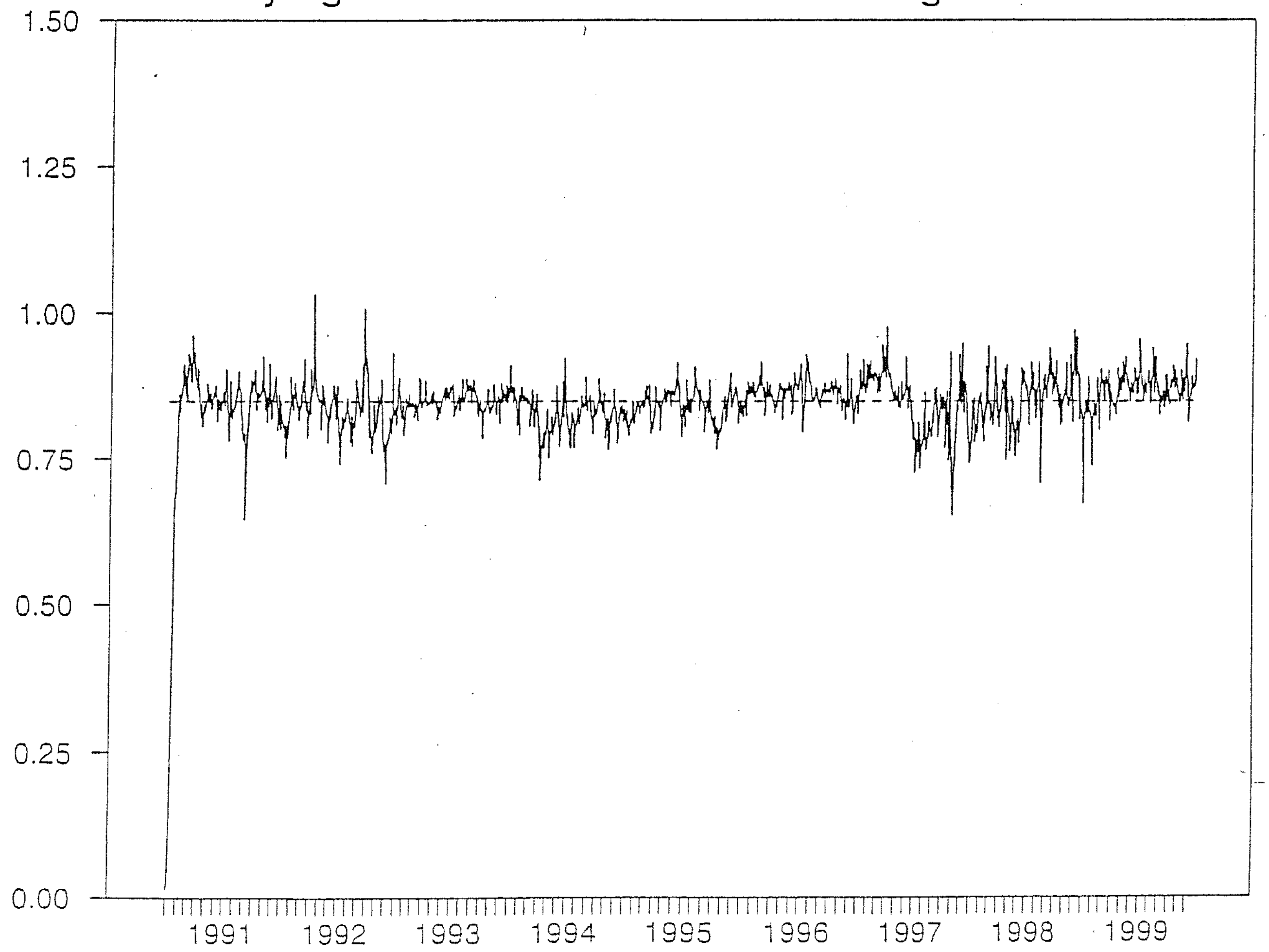


Figure 5.7

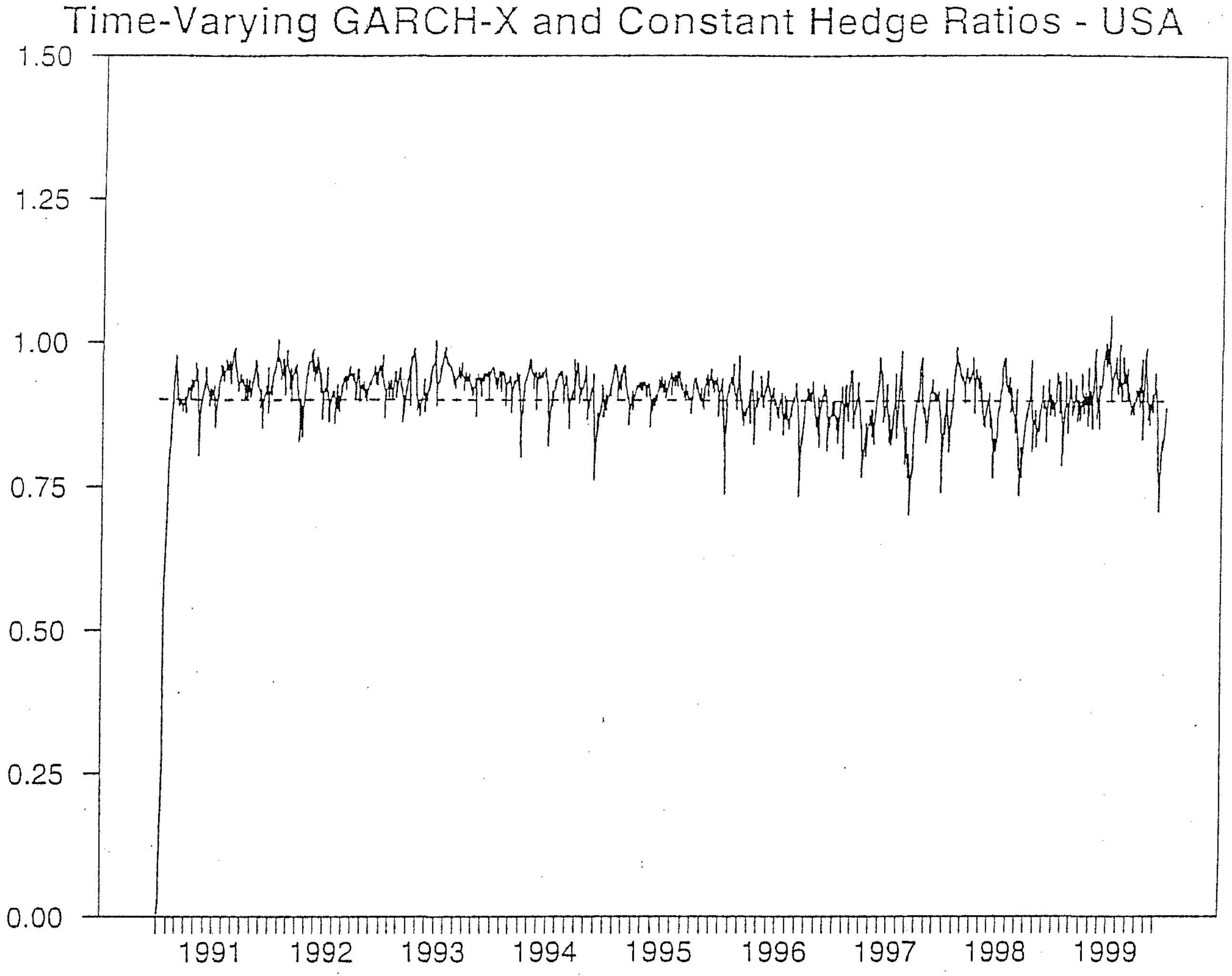

Time-Varying GARCH-X and Constant Hedge Ratios - USA
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1991
1992
1993
1994
1995
1996
1997
1998
1999

Figure 5.8

Table 5.21

Summary Statistics for Stock Index Futures Markets (GARCH Model Hedge Ratios)

	Obs	Mean	Std Error	Variance	Min	Max	Range
Australia	2348	0.69899	0.07032	0.00494	0.00959	0.95416	0.94457
Germany	2348	0.78765	0.09252	0.00856	0.00772	1.19716	1.18944
Hong Kong	2348	0.79991	0.10357	0.01072	-0.01687	1.36871	1.38558
Japan	2348	0.94401	0.07303	0.00533	0.01807	1.45793	1.43923
South Africa	2348	0.57839	0.10658	0.01136	0.0094	1.01373	1.00433
UK	2348	0.84219	0.06375	0.00406	0.01477	1.03205	1.01728
US	2348	0.90437	0.07498	0.00562	0.00562	1.04679	1.04117

Table 5.22

Summary Statistics for Stock Index Futures Markets (GARCH-X Model Hedge Ratios)

	Obs	Mean	Std Error	Variance	Min	Max	Range
Australia	2348	0.70321	0.06647	0.00441	-0.06494	1.06096	1.13454
Germany	2348	0.78700	0.09648	0.00931	0.00765	1.20061	1.19296
Hong Kong	2348	0.80566	0.09110	0.0083	0.02393	1.33119	1.30726
Japan	2348	0.94796	0.07379	0.00544	0.02313	1.45899	1.43586
South Africa	2348	0.58351	0.10691	0.01143	0.00796	1.05511	1.04715
UK	2348	0.84324	0.06118	0.00374	0.01593	1.03368	1.01775
US	2348	0.90374	0.07461	0.00556	0.00547	1.04526	1.03979

5.2 TWO OUT-OF-SAMPLE TIME PERIOD RESULTS.

5.2.1 One Year Out-of-Sample Time Period (1st Jan 1999 to 31st Dec 1999).

This section investigates out-of-sample performance. One and two years out-of-sample time periods are selected. As the length of the within-sample time period is a 9 year period, two overlapping periods of one and two years were used for comparison. These periods are selected in order to check if changing the length and time of the out-of-sample periods has any affect on the inferences. The one year out-of-sample data used covers the period from 1st January 1999 to 31st December 1999. Both GARCH and GARCHX models are estimated for the period 1st January 1991 to 31st December 1998 so that we can use the parameters from this time period to estimate the portfolio for the one year out-of-sample period.

In order to avoid the problem of spurious regression we investigated the stochastic structure of the out-of-sample time period data. As in the within-sample period in section 5.1.2, the ADF and KPSS tests are applied. The test results are not presented here but are available on request. For the ADF test, the null is the presence of a unit root while in the KPSS test, the null hypothesis is the absence of unit roots. Using the ADF test for the one year out-of-sample time period all series are found to be non-stationary in levels and stationary after first difference except for the Australian series. For the Australian series, in the first order integration test the coefficients are found to be negative and significant for the cash and futures series for the 1st January 1991 to 31st December 1998 period. Hence, the Australian series are found to be stationary in levels and stationary after first difference. This result is similar to the full sample results. Therefore, we apply the KPSS tests to confirm the stochastic structure of the data for the same period. For the KPSS tests all series are found to be non-stationary in levels and stationary after first difference. These results confirm that all of the data tested are non-stationary in levels and stationary after first difference. Once again this result is similar to the within-sample results.

Table 5.23 shows results from the Ordinary Least Squares method. Once again the following relationship is estimated by means of OLS:

$$r_t^c = \alpha + \beta r_t^f + \varepsilon_t$$

The OLS method between cash return and futures return is applied to estimate the minimum variance constant hedge ratios for the period 1st January 1991 to 31st December 1998 for use in the one year out-of-sample time period. In all cases, the hedge ratio is positive and significant. The hedge ratios range from 0.6197 to 0.9361 in the cases of South Africa and Japan, respectively.

As stated in section 4.3 of chapter 4, cointegration implies that linear combinations of two or more non-stationary variables converge to an equilibrium in the long run. The cointegration test results for the out-of-sample time period are not presented. For all countries, cointegration is found between cash index and futures index. As in the within-sample time period the error correction term from the cointegration relationship for this time period is subsequently applied in the GARCH-X model.

The GARCH and GARCHX estimation results are presented in Tables 5.24, 5.25, 5.26 and 5.27. Model specifications were presented in sections 4.4 and 4.5 of chapter 4. Both GARCH and GARCHX models are estimated for the period 1st January 1991 to 31st December 1998 so that we can use the parameters from this time period to construct the portfolio for the one year out-of-sample period. Significant ARCH process coefficients (A_{11} and A_{22}) are found in all cash and futures series. From both GARCH and GARCH-X results, the ARCH process in both cash and futures series are significant and less than one in all cases. The positive and significant coefficients of B_{11} and B_{33} indicate the existence of the GARCH effect in both GARCH and GARCH-X results. Positive and significant covariance coefficients (A_{22} and B_{22}) show that cash and futures prices are correlated in all of the markets involved. This implies a strong interaction between cash and futures for the one year time period (1st January 1991 to 31st December 1998). From the GARCH results in Tables 5.24 and 5.25 the highest persistence of shocks to volatility is 0.9457 in Germany and the lowest is 0.8336 in the UK for the cash markets, while in the futures markets the highest persistence is 0.9539 in Hong Kong and the lowest is 0.8615 again in the UK. Meanwhile, in the GARCH-X cases in Tables 5.26 and 5.27 the lowest persistence is in Australia and the highest in South Africa for the cash markets, but in the futures markets the persistence is highest for Hong Kong and lowest in the case of Australia once again. The MA terms in both the GARCH and GARCH-X cases are negative and significant in the South African cash series only and positive in the other cases for both cash and futures series. The significance of the MA terms may be due to non-synchronous trading as discussed previously in the full sample period (section 5.1.4). In this study, Ljung-Box statistics of order 6 are used to detect the serial correlation for both cash and futures series[14]. From the GARCH-X results in Tables 5.26 and 5.27 the squared error correction terms (D_{11}, D_{22} and D_{33}) are positively related to the conditional variance in all the series involved except in the Germany case where the error correction term is significant and negative. Negative effects indicate that an increase in the short-run deviations from a long-run relationship between spot and futures prices reduces the volatility. A positive and significant error correction term increases the volatility between spot and futures prices. These results are quite similar to full sample period results.

5.2.1.1 Comparison of the hedge ratios (1st Jan 1999 to 31st Dec 1999).

The investigation of hedging effectiveness[15] for the out-of-sample time period is conducted after the estimated parameters for OLS, GARCH and the GARCH-X models are applied to calculate the hedge ratios and the portfolios for the out-of-sample time period. The results in Table 5.28, for the one year out-of-sample period clearly show that the GARCH method outperforms all the other methods in every case with the single exception of the Japanese case for the minimum variance method, which marginally outperforms the GARCH method by less than 1%. Recalling the within-sample results from the previous section, the GARCH method outperformed the unhedged and traditional method in every case except in the Japanese series where the traditional methods outperformed the GARCH method slightly. The GARCH methods compared better with the minimum variance in some cases while underperformed in other cases. Hence, from the Table

---

[14]No serial correlation at higher order than 6 was found, therefore GARCH(1,1) and GARCHX(1,1) are suitable for this research study. The results for the serial correlation tests are available if required.

[15]As discussed earlier in section 5.1.4.1 for the full sample period, hedging effectiveness for the methods involved is compared using the variance of the estimated portfolios and the change in the variance.

5.28, the performance of the GARCH model time-varying hedge for the one year out-of-sample time period is much better than for the within-sample time period. The percentage changes in variance are larger in the out-of-sample than the within-sample period.

The hedged methods in the out-of-sample tests show higher percentage change than the within-sample tests in most cases. From Tables 5.15 and 5.28, the GARCH model for one year out-of-sample period outperforms all constant methods for every case except in the Japan case for minimum variance method, where the GARCH model underperforms by less than 1%. Whereas, for the within-sample period the GARCH model underperforms in Germany, Japan, UK and the USA compared to the minimum variance method, also underperforms in the Japan case in comparison to the traditional method. From Tables 5.15 and 5.28, it is quite clear that hedging using GARCH for the out-of-sample period reduces risk more than not hedging at all.

Turning to the comparison between the GARCH-X hedge ratio method and all other methods shown in Table 5.29, the GARCH-X method outperforms the unhedged method and the traditional method in all cases. The GARCH-X method performs better than the minimum variance method in all the cases except in Japan where the minimum variance model outperforms the GARCH-X marginally. For the one year out-of-sample time period, the GARCH-X outperforms the GARCH method in the cases of Australia, Germany, Japan, South Africa and USA, but slightly underperforms compared to the GARCH model in the cases of Hong Kong and the UK. Hence, in most cases, the error correction term of short-run deviations from a long-run cointegrated relationship between cash and futures prices improves the time-varying hedge ratio when linked to the GARCH-X model in most cases. Recalling the within-sample results, the GARCH-X model outperformed the GARCH model in the cases of Australia, Japan, the UK and the US, but it underperformed in the other cases. The GARCH-X models outperformed the unhedged and traditional hedge in all cases except the Japanese case for the traditional method. Moreover, the GARCH-X method for the within-sample time period performed better in comparison to the minimum variance hedge methods in the cases of Australia, Hong Kong and South Africa but it underperformed in the other cases. From Tables 5.29 and 5.20, the GARCH-X model performs better than the other methods for the one year out-of-sample time period in most cases compared to the within-sample time period.

As for the GARCH case, the variance reduction is more effective with GARCH-X for the out-of-sample time period in most cases as compared to the with-in-sample period. Both within-sample and out-of-sample evidence presented indicates that the hedging strategy using bivariate GARCH and GARCH-X methods are potentially superior to the other conventional methods. The transaction cost may be too high for frequent reconstructing of the portfolios to compute time-varying optimal hedge ratios. Daily reconstructing of the portfolios in this empirical work gives varying results. Given that, the investor should hedge with the appropriate hedging methods using the percentage change in variance. From the Table 5.29 the portfolio manager may opt to use the constant minimum hedge method instead of reconstructing the daily portfolios which may be proved to be too costly. According to that, the trade off between the risk reduction and transactions cost will determine the practicality of the hedging strategy used by the portfolio manager. Further insights are provided in chapter 7.

5.2.2 Two Year Time Period (1st Jan 1998 to 31st Dec 1999).

The two year out-of-sample period ranges from 1st January 1998 through to 31st December 1999. To investigate the hedging effectiveness for the two year out-of-sample time period, we have to estimate the parameters for the time period 1st January 1991 to 31st December 1997, which is then applied to calculate the hedge ratios and the portfolios for the two year out-of-sample time period. For the ADF, KPSS, and cointegration tests for 1st January 1991 to 31st December 1997 we find similar results to those for the 1st January 1991 to 31st December 1998 period. Again, results from these tests are not presented in the interests of brevity, but are available on request. In both ADF and KPSS tests, all series are found to be non-stationary in levels and stationary after first difference except for the Australian futures series from the ADF tests, where the series is found to be stationary in levels at the 10% level. Again cointegration is found for all countries. From Table 5.30, the minimum variance estimation shows that for 1st January 1991 to 31st December 1997 the hedge ratios estimated by the OLS model range between 0.5698 to 0.9449 in South Africa and Japan, respectively.

The GARCH and GARCH-X results are presented in Tables 5.31, 5.32, 5.33 and 5.34. Once again the size of the ARCH parameters (A_{11} and A_{33}) are significant and less than one in the cash and futures markets in all cases. The GARCH effect is also positive and significant in all cases. From the GARCH and GARCH-X results there is strong evidence of interaction between cash and futures prices. It is clearly seen in the GARCH results that the persistence of shocks to volatility for cash and futures markets is less than one in all cases, and ranges between 0.5929 and 0.9308 in the UK and Germany for the cash markets, and ranges between 0.79747 in the UK and 0.9311 in Japan for the futures markets. In the GARCH-X results, the persistence of cash and futures prices are positive and significant in all cases. In cash and futures markets, if the persistence terms ($A_{11} + B_{11}$, $A_{33} + B_{33}$) are less than one, then $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are covariance stationary. The MA term is positive in all series involved except in the South African cash returns for both the GARCH and GARCHX results. In the cases of GARCH and GARCH-X methods there is no serial correlation in all series for the higher order. In the GARCH-X model the effect of the short-run deviations between the cash and futures prices from a long run cointegrated relationship on the covariance (D_{22}) are negative in the cases of Germany, Hong Kong and South Africa. This indicates that the short-run deviations reduce volatility.

5.2.2.1 Comparison of the hedge ratios (1st Jan 1998 to 31st Dec 1999).

In Table 5.35, the time varying GARCH method reduces the variance by a high percentage compared to the constant methods in all cases except the UK and the US in the minimum variance method, where the GARCH method was outperformed. In Table 5.36 the GARCH-X method compared well to the unhedged and traditional methods in all cases. This method also compares favourably to the minimum variance hedge ratios in the cases of Germany, Hong Kong, Japan and South Africa, but not in the cases of Australia, UK and US. The GARCH-X method does better than the GARCH method in the cases of Germany, Hong Kong and Japan, while it underperforms in comparison to the GARCH model in the other cases. Comparing the results with those in Tables 5.28 and 5.29, increasing the out-of-sample period by one more year shows that the GARCH method underperforms in the cases of the UK and the US, while slightly outperforms in the Japanese case. Similarly in the GARCH-X method, increasing the sample size shows that the time-varying GARCH-X model underperforms in Australia, the UK and the US in comparison to the minimum variance methods. It also underperforms in Australia, South

Africa, the UK and the US compared to the standard GARCH model. While the increase in the out-of-sample time period sample shows that the GARCH-X out performs the one year period in the Hong Kong series slightly.

A comparison between the two year period and the within-sample period shows that the GARCH methods compared significantly better in the two year out-of-sample period in almost all the cases. The GARCH is outperformed in the UK and the US only in comparison to the minimum variance methods in the two year period. While, in the within-sample time period the GARCH method was out performed by 2.95% in comparison to the traditional methods and also outperformed in Germany, Japan, the UK and the US in comparison to the minimum variance. Meanwhile, the GARCH-X in the two year out-of-sample period outperforms the unhedged and traditional method but underperforms in cases of Australia, the UK and US compared to the minimum variance. Moreover, the GARCH-X outperforms the GARCH method in the cases of Germany, Hong Kong and Japan. Again in the within-sample period the GARCH-X method underperforms in the Japanese case compared to the traditional method and underperforms in Germany, Japan, the UK and the US compared to the minimum variance. The GARCH-X is also outperformed by the GARCH method in cases of Germany, Hong Kong and South Africa, however, the GARCH-X does better in the other cases in the two year out-of-sample period. Regardless of the size of reduction in risk for most cases the time-varying hedge ratio performs better than the constant ratios in reducing risk. Comparing the two out-of-sample periods, the reduction in risk is of larger magnitude for the one year out-of-sample period. Tables 5.28, 5.29, 5.35 and 5.36 for the GARCH and GARCH-X methods show that both models in the one year period compared better than the same methods in the two year periods. Thus, it is clearly seen that reducing the out-of-sample time period increases the effectiveness of the time varying methods of the GARCH and GARCH-X. Considering the high transaction cost of reconstructing a portfolio daily, the portfolio manager may hedge using the time-varying methods when the reduction of variance is substantial[16], as the trade off between the risk reduction and the transactions cost will determine the practicality of the time-varying hedge method.

---

[16]Achieving large risk reduction may imply that the trade off with the transaction costs is worthwhile, which gives portfolio manager the incentive to adjust the portfolio on daily basis.

5.3 Conclusion

In order to gain further insights on the trade off between risk reduction and transaction costs, the out-of-sample cases where the time-varying hedge ratio methods out-perform the minimum variance hedge ratio will be investigated in chapter 7. The investigation is conducted to determine whether the time-varying method offers improved hedge efficiency after accounting for transaction costs. The empirical investigation is carried out between the minimum variance, GARCH and GARCH-X methods for one and two years out-of-sample time periods.

Table 5.23

OLS Test Results For (1st January 1991 to 31st December 1998) Time Period

Countries	α	β	R^2	D.W.
Australia	0.000206[a] (2.3713)	0.6805[a] (81.667)	0.7617	2.4162
Germany	0.000283[c] (1.7983)	0.7504[a] (58.627)	0.6222	2.7835
Hong Kong	0.0000403 (0.2695)	0.8159[a] (107.78)	0.8477	2.5203
Japan	0.000074 (0.6539)	0.93609[a] (117.32)	0.8683	2.6132
South Africa	0.000282[a] (2.4693)	0.6197[a] (71.6996)	0.7113	2.0666
UK	0.00017[a] (2.8689)	0.8372[a] (137.990)	0.9012	2.3591
USA	0.000197[a] (3.8985)	0.8919[a] (155.941)	0.9209	2.5394

Notes:
t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%.

Table 5.24

BGARCH Results For (1^{st} January 1991 to 31^{st} December 1998) Time Period

Parameters	Australia	Germany	Hong Kong
α_1	0.00045172[a] (2.88735)	0.00072148[a] (4.22025)	0.0010696[a] (4.02409)
θ_1	0.0755[a] (4.47095)	0.22047[a] (11.07133)	0.0765[a] (4.62575)
α_2	0.00032890[a] (1.92226)	0.00055361[a] (3.48245)	0.0010670[a] (4.15724)
θ_2	0.2186[a] (13.05257)	0.3598[a] (20.42194)	0.2075[a] (12.65652)
C_1	0.0000059954[a] (12.05514)	0.0000073731[a] (9.89622)	0.000013598[a] (18.03191)
A_{11}	0.0787[a] (14.55785)	0.0984[a] (11.90332)	0.1280[a] (17.30085)
B_{11}	0.8291[a] (87.57032)	0.8473[a] (74.72650)	0.8198[a] (129.12150)
C_2	0.000008621[a] (12.26729)	0.0000084132[a] (13.67726)	0.000013009[a] (14.19357)
A_{22}	0.0818[a] (12.46724)	0.0798[a] (12.40561)	0.1029[a] (16.25190)
B_{22}	0.8024[a] (70.00307)	0.8503[a] (93.01297)	0.8445[a] (131.35996)
C_3	0.000014704[a] (10.36698)	0.000012693[a] (15.16723)	0.000013555[a] (10.79863)
A_{33}	0.0892[a] (10.52035)	0.0943[a] (11.62276)	0.0921[a] (15.73543)
B_{33}	0.7738[a] (47.48038)	0.8252[a] (76.32910)	0.8618[a] (121.81945)
L	19273.22	18000.49	17352.9

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.25
BGARCH Results For (1st January 1991 to 31st December 1998) Time Period

Parameters	Japan	South Africa	UK	US
α_1	0.00015392 (0.78937)	0.0007581[a] (4.68378)	0.0005948[a] (4.19800)	0.00069144[a] (5.73111)
θ_1	0.22532089[a] (13.87382)	-0.08611[a] (-4.11374)	0.1126324[a] (6.07886)	0.1973[a] (10.64404)
α_2	0.00005169 (0.26310)	0.0003974 (1.94531)	0.0004602[a] (3.16802)	0.00058203[a] (4.91577)
θ_2	0.2482242[a] (15.52760)	0.08105[a] (4.12810)	0.1916341[a] (11.01596)	0.2522[a] (13.69886)
C_1	0.000016021[a] (11.58060)	0.00000713[a] (17.08931)	0.00001140[a] (10.63163)	0.000004422[a] (12.15265)
A_{11}	0.12544018[a] (14.03574)	0.192[a] (19.09774)	0.1117053[a] (17.00814)	0.0774[a] (18.04404)
B_{11}	0.80190359[a] (69.09408)	0.711[a] (59.05048)	0.72191047[a] (45.69116)	0.8463[a] (108.4627)
C_2	0.000014841[a] (10.48251)	0.000007337[a] (17.15004)	0.00001211[a] (11.07103)	0.000004994[a] (12.56562)
A_{22}	0.10965083[a] (12.79055)	0.156[a] (18.88183)	0.10179726[a] (15.01558)	0.0814[a] (18.23248)
B_{22}	0.8148138[a] (66.86904)	0.743[a] (69.96928)	0.73491405[a] (50.60060)	0.8347[a] (107.5979)
C_3	0.000014881[a] (9.44009)	0.00001314[a] (15.80147)	0.000012338[a] (11.04492)	0.000005469[a] (12.5666)
A_{33}	0.108497109[a] (12.46687)	0.155[a] (19.67258)	0.09764097[a] (12.65034)	0.0898[a] (16.39850)
B_{33}	0.81849809[a] (63.47859)	0.746[a] (60.23348)	0.7643945[a] (55.72162)	0.8283[a] (103.46111)
L	18239.81	18573.82	20226.61	21018.13

Notes:
a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.26
BGARCH-X Results For (1st January 1991 - 31st December 1998) Time Period.

Parameters	Australia	Germany	Hong Kong
α_1	0.0004124355[a] (2.66601)	0.0007391[a] (4.27736)	0.0010360376[a] (3.89435)
θ_1	0.0688922729[a] (3.55719)	0.202[a] (10.77252)	0.0806848635[a] (4.68675)
α_2	0.0002896265 (1.767181)	0.0005552[a] (3.48795)	0.0010418459[a] (4.03556)
θ_2	0.205437874[a] (11.25081)	0.357[a] (20.23509)	0.2086051192[a] (12.48886)
C_1	0.0000281741[a] (8.86952)	0.000008030[a] (9.61262)	0.0000133845[a] (12.83537)
A_{11}	0.1382187919[a] (11.80044)	0.106[a] (12.15999)	0.1228524907[a] (16.35650)
B_{11}	0.3805994169[a] (7.12881)	0.834[a] (71.91502)	0.80622816[a] (122.82863)
C_2	0.0000294440[a] (9.05338)	0.000008993[a] (14.23593)	0.0000131574[a] (11.54196)
A_{22}	0.1249866962[a] (10.73034)	0.08318[a] (12.51596)	0.0987759762[a] (15.39941)
B_{22}	0.4474048778[a] (9.40956)	0.847[a] (93.25868)	0.8323176244[a] (118.35026)
C_3	0.0000355195[a] (9.03573)	0.00001314[a] (15.17583)	0.0000139702[a] (9.58237)
A_{33}	0.1173885004[a] (9.28286)	0.09499[a] (11.91085)	0.0885801428[a] (15.12911)
B_{33}	0.5227382504[a] (12.27377)	0.831[a] (77.93256)	0.8504054076[a] (107.72424)
D_{11}	0.0557982606[a] (3.03951)	0.001065[a] (0.10775)	0.0571276328[a] (6.30485)
D_{22}	0.0409757913[a] (2.30419)	-0.01314[a] (-1.54578)	0.0447457706[a] (4.59210)
D_{33}	0.0505035238[a] (2.52207)	-0.03207[a] (-3.79790)	0.04507272[a] (4.02513)
L	19274.94	18006.17	17374.6

Table 5.27
BGARCH-X Results For (1st January 1991 - 31st December 1998) Time Period

Parameters	Japan	South Africa	UK	USA
α_1	0.0001203488 (0.63319)	0.0007213[a] (4.16367)	0.0005726541[a] (3.90846)	0.00068193[a] (5.50601)
θ_1	0.2258336632[a] (13.84214)	-0.08896[a] (-4.26461)	0.1146480827[a] (6.02398)	0.1961[a] (10.54591)
α_2	0.0000077502 (0.04010)	0.0004473[a] (2.21301)	0.0004366866[a] (2.89651)	0.00056769[a] (4.63971)
θ_2	0.2482659545[a] (15.35502)	0.07672[a] (3.76797)	0.1935174419[a] (10.90445)	0.2505[a] (13.40791)
C_1	0.0000183586[a] (10.66611)	0.000006699[a] (14.67707)	0.0000112511[a] (9.94865)	0.0000043079[a] (11.45790)
A_{11}	0.1347167978[a] (13.11202)	0.176[a] (16.42383)	0.1148546037[a] (17.65596)	0.0777[a] (17.76862)
B_{11}	0.7649312781[a] (53.39140)	0.769[a] (60.41668)	0.6880813036[a] (37.172665)	0.8432[a] (106.77533)
C_2	0.0000174438[a] (9.80706)	0.000006253[a] (16.23074)	0.0000117748[a] (10.40450)	0.0000049508[a] (11.70266)
A_{22}	0.1160392288[a] (12.18156)	0.138[a] (16.44249)	0.1041420353[a] (15.21973)	0.0825[a] (17.67534)
B_{22}	0.7825614750[a] (51.72587)	0.758[a] (73.5922)	0.7094805635[a] (42.70494)	0.8277[a] (98.61533)
C_3	0.0000172686[a] (8.94746)	0.000009832[a] (12.71092)	0.0000119731[a] (10.40205)	0.0000055234[a] (11.74076)
A_{33}	0.1126799146[a] (12.02621)	0.134[a] (18.51642)	0.0996746137[a] (12.69855)	0.0919[a] (15.78480)
B_{33}	0.7927979564[a] (51.04003)	0.769[a] (60.41668)	0.7450723965[a] (49.53748)	0.8162[a] (91.35060)
D_{11}	0.1122642745[a] (3.50678)	0.0007479[a] (4.5694)	0.0748083380[a] (4.32234)	0.0293 (1.40144)
D_{22}	0.0685511460[a] (2.44357)	0.0008481[a] (3.88628)	0.0690427677[a] (4.21041)	0.0435 (1.86024)
D_{33}	0.0500651959[a] (1.91591)	0.001973[a] (5.92907)	0.0635321460[a] (4.05371)	0.0656[a] (2.39489)
L	18253.58	18601.38	20238.02	21022.79

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.28
BGARCH Vs Conventional Methods
One Year Out-Of-Sample Period (1st January 1999- 31st December 1999) BGARCH Results

part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
unhedged	0.00005784	0.000186	0.000268	0.000156	0.00009807	0.000123	0.000125
Traditional	0.00001368	0.00002949	0.000188	0.00002323	0.00003096	0.000006664	0.00001111
Minimum Var	0.00001053	0.00003201	0.000138	0.00002205	0.00001719	0.000006374	0.00001097
BGARCH	0.00001017	0.00002863	0.000105	0.00002217	0.00001678	0.000006002	0.00001086

Part B

Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	82.24	84.60	60.82	85.78	82.88	95.12	91.31
Traditional	25.65	2.91	44.14	4.56	45.80	9.93	2.25
Minimum Var	3.41	10.55	23.91	-0.54	2.38	5.83	1.00

Table 5.29
BGARCH-X Vs BGARCH and Conventional Methods
One Year Out-Of-Sample Time Period (1st January 1999- 31st December 1999) BGARCH-X Results

part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
unhedged	0.00005784	0.000186	0.000268	0.000156	0.00009807	0.000123	0.000125
Traditional	0.00001368	0.000186	0.000188	0.00002323	0.00003096	0.000006664	0.00001111
Minimum Var	0.00001053	0.00002949	0.000138	0.00002205	0.00001719	0.000006374	0.00001097
BGARCH	0.00001017	0.00003201	0.000105	0.00002217	0.00001678	0.000006002	0.00001086
BGARCHX	0.00001009	0.000028635	0.000107	0.00002213	0.00001675	0.000006100	0.00001085

Part B
Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	82.55	84.60	60.07	94.95	82.92	95.04	91.32
Traditional	26.24	2.9	43.08	4.73	45.89	8.46	2.34
Minimum Var	4.17	10.55	22.46	-0.36	2.55	4.29	1.10
Bi-GARCH	0.78	10.54	-1.90	0.18	0.17	-1.63	0.09

Table 5.30

OLS Results For (1st January 1991 to 31st December 1997) Time Period

Countries	α	β	R^2	D.W.
Australia	0.000224[a] (2.4139)	0.6717[a] (74.4770)	0.7524	2.4148
Germany	0.000322[b] (2.0332)	0.71606[a] (50.443)	0.5822	2.7996
Hong Kong	0.000130 (0.8991)	0.8029[a] (99.1258)	0.8433	2.5417
Japan	0.000083 (0.7038)	0.9449[a] (109.83)	0.8685	2.6703
South Africa	0.000357[a] (3.1679)	0.5698[a] (57.279)	0.6425	2.1233
UK	0.000186[a] (3.2338)	0.8206[a] (128.74)	0.9008	2.3918
USA	0.000163[a] (3.3556)	0.8941[a] (146.08)	0.9212	2.6043

Notes:

t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%

Table 5.31
BGARCH Results For (1st January 1991 - 31st December 1997) Time Period

Parameters	Australia	Germany	Hong Kong
α_1	0.00045277[a] (2.72581)	0.00064719[a] (3.73009)	0.0011484[a] (4.17108)
θ_1	0.0707[a] (3.87077)	0.2254[a] (11.15800)	0.06677908[a] (3.58503)
α_2	0.00030966 (1.68880)	0.00046221[a] (2.85737)	0.0011327[a] (4.30475)
θ_2	0.2113a (11.56468)	0.3826[a] (20.76615)	0.207062[a] (11.65176)
C_1	0.000005955[a] (11.74425)	0.000008262[a] (9.76466)	0.00002386[a] (11.70481)
A_{11}	0.0770[a] (13.73386)	0.0953[a] (11.14759)	0.1417317[a] (14.42665)
B_{11}	0.8276[a] (84.43216)	0.8355[a] (66.87426)	0.739063[a] (49.06280)
C_2	0.0000086404[a] (12.04348)	0.00000881[a] (13.12132)	0.00002149[a] (10.81673)
A_{22}	0.0804[a] (11.57057)	0.0716[a] (10.56498)	0.1105041[a] (13.56920)
B_{22}	0.7989[a] (66.99506)	0.8466[a] (84.54644)	0.782944[a] (58.11454)
C_3	0.000014962[a] (10.13971)	0.00001282[a] (12.10990)	0.00002123[a] (10.04890)
A_{33}	0.0891[a] (9.88478)	0.0820[a] (9.52479)	0.0975796[a] (13.59682)
B_{33}	0.7675[a] (44.35989)	0.8265[a] (61.31564)	0.8156115[a] (68.03053)
L	16883.91	15961.37	15482.84

Table 5.32
BGARCH Results For (1st January 1991 - 31st December 1997) Time Period

Parameters	Japan	South Africa	UK	USA
α_1	0.0001972 (1.00382)	0.0006155[a] (3.47898)	0.0005660[a] (3.86537)	0.00057861[a] (4.56868)
θ_1	0.2414108[a] (13.78742)	-0.09593[a] (-4.37693)	0.1296573[a] (6.58105)	0.1968[a] (10.25664)
α_2	0.00008318 (0.41532)	0.0003260 (1.53987)	0.00043371[a] (2.90907)	0.0004823[a] (3.89885)
θ_1	0.2590593[a] (14.90966)	0.08150[a] (3.48316)	0.208592[a] (11.77775)	0.2565[a] (13.29777)
C_1	0.00001152[a] (11.38259)	0.00000763[a] (15.00053)	0.00002506[a] (11.86634)	0.000004657[a] (14.16252)
A_{11}	0.12958092[a] (13.65448)	0.155[a] (12.99265)	0.086623[a] (10.09998)	0.0641[a] (16.16245)
B_{11}	0.7996944[a] (67.76267)	0.699[a] (43.97165)	0.506298[a] (16.69713)	0.8469[a] (127.44908)
C_2	0.00001368[a] (9.96512)	0.00000766[a] (15.20399)	0.00002168[a] (12.64558)	0.00000574[a] (12.6573)
A_{22}	0.1098711[a] (12.40345)	0.132[a] (13.9446)	0.0695031[a] (8.62297)	0.0715[a] (16.09588)
B_{22}	0.8176916[a] (65.85978)	0.731[a] (53.04879)	0.6113389[a] (27.41415)	0.8213[a] (94.38838)
C_3	0.00001323[a] (8.77684)	0.0000142[a] (13.68363)	0.00001666[a] (14.04077)	0.000006531[a] (11.12833)
A_{33}	0.10411104[a] (11.98146)	0.138[a] (17.02067)	0.0619455[a] (7.61480)	0.0808[a] (14.25879)
B_{33}	0.8270059[a] (63.53021)	0.730[a] (45.8995)	0.735525[a] (47.38832)	0.8093[a] (71.74288)
L	16107.57	16539.42	17925.81	18604.81

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.33
BGARCH-X Results For (1st January 1991 - 31st December 1997) Time Period

Parameters	Australia	Germany	Hong Kong
α_1	0.00041153[a] (2.51828)	0.0006687[a] (3.79652)	0.001134[a] (4.13142)
θ_1	0.06748315[a] (3.11066)	0.223[a] (10.89768)	0.07312[a] (3.72741)
α_2	0.00027489[a] (1.48565)	0.0004621[a] (2.84157)	0.0011332[a] (4.30617)
θ_2	0.20170442[a] (10.01692)	0.379[a] (20.28226)	0.209[a] (11.50170)
C_1	0.00002947[a] (8.74094)	0.000008975[a] (9.46353)	0.00003092[a] (11.30766)
A_{11}	0.1335089[a] (11.21895)	0.102[a] (11.08339)	0.149[a] (13.68330)
B_{11}	0.3227731[a] (5.32757)	0.818[a] (61.51074)	0.699[a] (39.10200)
C_2	0.00003017[a] (8.69207)	0.00001295[a] (12.00094)	0.00002824[a] (11.26069)
A_{22}	0.1189489[a] (9.86550)	0.07468[a] (10.48478)	0.115[a] (13.46082)
B_{22}	0.4093507[a] (7.55891)	0.842[a] (78.65753)	0.752[a] (49.56921)
C_3	0.00003575[a] (8.90241)	0.00001295[a] (12.00094)	0.00002733[a] (11.08680)
A_{33}	0.1129287[a] (8.59140)	0.08425[a] (9.87755)	0.09955[a] (13.67709)
B_{33}	0.5056337[a] (11.11604)	0.832[a] (62.32110)	0.794[a] (62.80366)
D_{11}	0.0724138[a] (3.52633)	0.01213[a] (1.00354)	-0.01616 (-1.07415)
D_{22}	0.0566869[a] (2.87839)	-0.00410 (-0.41292)	-0.03076[a] (-2.13700)
D_{33}	0.0621496[a] (2.90714)	-0.02396[a] (-2.45289)	-0.02744 (-1.94203)
L	16891.09	15966.15	15497.11

Table 5.34
GARCH-X Results For (1st January 1991 - 31st December 1997) Time Period

Parameters	Japan	South Africa	UK	USA
α_1	0.00014575 (0.76907)	0.0006146[a] (3.43299)	0.00053611[a] (3.54659)	0.00070631[a] (5.43965)
θ_1	0.2428611[a] (1364808)	-0.09882[a] (-4.63039)	0.13610356[a] (6.83062)	0.2076[a] (10.19110)
α_2	0.00002149 (0.11018)	0.0004006 (1.96196)	0.00039917[a] (2.57871)	0.00058859[a] (4.68327)
θ_2	0.26144696[a] (14.73020)	0.07613[a] (3.35041)	0.21263580[a] (11.620039)	0.2605[a] (13.54382)
C_1	0.00001697[a] (10.36157)	0.000007243[a] (13.61100)	0.00002370[a] (13.01558)	0.00001673[a] (12.36476)
A_{11}	0.1327723[a] (12.79604)	0.150[a] (13.78730)	0.0846179a (9.77914)	0.0985[a] (12.26022)
B_{11}	0.7659184[a] (53.39482)	0.716[a] (49.17058)	0.4546416[a] (18.50492)	0.5559[a] (20.29846)
C_2	0.00001592[a] (9.20499)	0.000006648[a] (14.87340)	0.00001952[a] (14.24572)	0.000014112[a] (12.31277)
A_{22}	0.1111365[a] (11.7563)	0.122[a] (15.67696)	0.06788337[a] (8.34199)	0.0919[a] (12.89534)
B_{22}	0.7869340[a] (51.05080)	0.761[a] (66.04193)	0.59070588[a] (34.32336)	0.6318[a] (28.07088)
C_3	0.00001563[a] (8.13690)	0.00001046[a] (11.53903)	0.00001540[a] (14.18061)	0.000011178[a] (13.01998)
A_{33}	0.1052253[a] (11.52147)	0.127[a] (18.57936)	0.06228853[a] (7.59105)	0.0869[a] (12.45078)
B_{33}	0.7986815[a] (49.97016)	0.766[a] (53.39086)	0.7144144[a] (47.86131)	0.7175a (44.25593)
D_{11}	0.1219668[a] (3.69172)	-0.0001460[a] (-0.82273)	0.1475529[a] (6.76675)	0.2705[a] (5.01622)
D_{22}	0.0792601[a] (2.69302)	-0.0001814 -0.66317	0.1142318[a] (6.32272)	0.1728[a] (4.03064)
D_{33}	0.0650093[a] (2.30219)	0.001301[a] (3.61500)	0.0903491[a] (5.76675)	0.1099[a] (3.28426)
L	16122.16	16575.06	17953.17	18598.22

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 5.35

BGARCH Versus Conventional Methods
Two Year Out-of-Sample Time Period (1st January 1998- 31st December 1999) GARCH Results

part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
unhedged	0.00007112	0.000257	0.000501	0.000217	0.000202	0.000147	0.0000141
Traditional	0.00001927	0.00006381	0.000155	0.00003118	0.00006240	0.00001265	0.00001301
Minimum Var	0.00001338	0.00006485	0.000120	0.00002932	0.00004054	0.00001175	0.00001174
BGARCH	0.00001251	0.00005958	0.000106	0.00002917	0.00003527	0.00001225	0.00001188

Part B
Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	82.41	76.81	78.84	86.55	82.53	91.66	15.74
Traditional	35.08	6.62	31.61	6.44	13.43	3.16	8.68
Minimum	6.50	8.12	11.66	0.51	12.99	-4.25	-1.10

Table 5.36

BGARCH-X Versus BGARCH and Conventional Methods
Two Year Period (1st January 1998- 31st December 1999) BGARCHX Results
part A
variance of the portfolio

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
unhedged	0.00007112	0.000257	0.000501	0.000217	0.000202	0.000147	0.0000141
Traditional	0.00001927	0.00006381	0.000155	0.00003118	0.00006240	0.00001265	0.00001301
Minimum Var	0.00001338	0.00006485	0.000120	0.00002932	0.00004054	0.00001175	0.00001174
BGARCH	0.00001251	0.00005958	0.000106	0.00002917	0.00003527	0.00001225	0.00001188
BGARCHX	0.00001358	0.00005900	0.000103	0.00002916	0.00003713	0.00001237	0.00001251

Part B
Percentage Change in Variance

Hedge Type	Australia	Germany	Hong Kong	Japan	South Africa	UK	USA
Unhedged	80.90	77.04	79.44	86.56	81.61	91.58	11.27
Traditional	29.52	7.53	33.54	6.47	62.33	2.21	3.84
Minimum	-1.49	9.02	14.16	0.54	8.41	-5.27	-6.15
Bi-GARCH	-8.55	0.97	2.83	0.03	-5.27	-0.97	-5.30

CHAPTER SIX

6.0 EMPIRICAL RESULTS FROM COMMODITY MARKETS.

The objective of this empirical chapter is to present quantitative evidence on the role of hedging to reduce risk using commodity futures contracts. There is little disagreement in the literature that hedging can be an effective risk management instrument in commodity markets. The motive for this chapter is to estimate the hedging effectiveness using a different asset class than the stock index futures applied in chapter 5. As the inherent nature of the stock and commodity markets are very different the results can potentially be very different. The aim of this chapter is to investigate how effective are the commodity futures markets to reduce risk compared to the stock futures markets results. This investigation aims to establish whether investors can improve portfolio performance across futures markets for different asset classes. This chapter focuses on the role of commodity futures in improving the hedging performance for the following markets: one Agriculture (Cocoa), one Metal (Aluminium) and three Crude Oil, namely West Texas Intermediate (O1), Brent Crude (O2) and Gas Oil EEC (O3).

We examine these commodity futures because they represent a unique asset for diversification purposes. Jensen et al (2000) noted that unlike financial securities, making a direct investment in physical commodities generally is unrealistic, and characterised by high transaction costs, insurance costs, and storage costs. In contrast, it is relatively easy to purchase and sell commodity futures contracts as a portfolio component. Meanwhile, Edwards and Park (1996) pointed out that the attraction of commodity futures to investors is based partially on the view that commodity prices tend to have low correlations with stock market returns, and thus provide diversification benefits.

The hedging effectiveness of commodity futures are highlighted in the empirical results of this chapter. The analysis employed several conventional and time-varying hedging methods. A hedging objective is likely to vary for different markets rather than follow an identical set of objectives. Indeed, it is likely that many investors are themselves unclear about where they should be in the range of hedging objectives in commodity markets. Commodity markets participants experience a wide range of risks from commodity price changes. In many areas that risk is increasing as markets are freed from regulations (Krapels and Pratt, 1998). For most commodity markets, risk is the reality of tomorrow's markets. Investors that apply hedging wisely are likely to succeed relative to those that fail to do so. This is true for the use of all futures contracts. The aim of the empirical investigation is to identify the hedging effectiveness in the sample of commodity futures markets under study.

6.1 WITHIN-SAMPLE TIME PERIOD RESULTS.

6.1.1 Commodity Cash and Futures Data.

Commodities are the basic raw materials that the world needs in order to function. The commodity data applied in this particular chapter are one agriculture, three energy and one metal. Many businesses trade in these commodities on a cash basis; prices fluctuate according to supply and demand. Commodity prices are unpredictable, as prices can be affected by all kind of events such as wars, strikes, climate, plagues, changes in consumer buying patterns and the activities of financial interests which may influence the market. Buyers and sellers of commodities may sell/buy a contract to deliver a product at some time in the future at an agreed price, thus taking the uncertainty out of their operations[1], where the hedgers are able to offset gains or losses in the cash market by an opposite effect in the futures market, and are thus able to run their businesses more steadily. As in the stock markets, an essential feature of commodity hedging is that the trader synchronises his/her activities in two markets, such as cash and futures markets.

Fundamentally, commodity price behaviour over time is a mixture of systematic fluctuations and randomness, while the variability of prices depends on information flows regarding supply and demand. As in the stock markets, the commonly used hedging methods are the conventional methods in the form of traditional, minimum variance and the unhedged methods. An implication from this is that not only the mean and constant variance may be used as a form of information, but also time-varying variance and higher moments are valuable information for risk

[1]See section 2.2 of chapter 2.

management. Hence, once again time-varying hedging methods are also undertaken to estimate the hedge ratios which are then compared to the conventional hedging methods used. Like in the stock futures markets, commodity futures markets enable management of risk and uncertainty. Futures contracts are used primarily for hedging, while an understanding of basis relationships and basis risk are important for hedging effectiveness.

In this empirical chapter there are five different commodity futures markets to be examined. Daily data of cash and futures prices are obtained from DATASTREAM. The commodity futures involved represent one agriculture, three energy and one metal markets. These data consist of Aluminium, Cocoa and three Crude Oil series which are identified as West Texas Intermediate (O1), Brent Crude (O2) and Gas Oil EEC (O3). The data involved in this chapter are relying on the data availability, while aiming to cover three traditional markets and within those selecting representatives of well traded commodities. The format of this data is similar to the stock markets data (section 5.1.1 of chapter 5) with different time period lengths. The within-sample commodity futures data used in the empirical analysis ranges from 1st January 1990 to 31st December 2000 for each series. All futures price indices are continuous series[2]. Again as in the stock markets, care is taken to ensure that all calculated futures returns are based on prices from contracts with the same delivery data.

Basic statistics for five cash and five futures commodity returns are shown in Table 6.1, where the unconditional distributions of the cash and futures price changes are non-normal, as evidenced by high skewness and high kurtosis. The cash series of O1, O2, O3 and Aluminium along with the futures series of the three Oil series are skewed to the left, while Cocoa cash and futures and Aluminium futures skewed to the right. All series of cash and futures returns are leptokurtic due to the presence of high kurtosis. The Aluminium cash and futures returns have the lowest variance while the O1 cash and futures have the highest.

[2]The continuous series starts at the nearest contract month which forms the first values for the continuous series until the contract reaches its expiry date, at this point the next trading contract month is taken.

6.1.2 Unit Root Tests.

6.1.2.1 Augmented Dickey-Fuller (ADF) Test Results.

As in the stock markets cases in chapter 5, all commodity cash and futures price indices and returns are tested for the presence of a unit root. The ADF test is applied using equation 4.9 from section 4.2.1 of chapter 4 and the results are presented in Table 6.2. Once again the first order integration test is testing for trend stationarity and the second order integration is testing for stationarity around the mean. According to the ADF test, all cash and futures price series are non-stationary in levels, but are stationary after first difference. The ADF test includes lags of the dependent variable in order to reduce serial correlation, and results with the lowest number of lags with no serial correlation are presented. These results are similar to the stock markets results presented in chapter 5.

6.1.2.2 KPSS Test Results.

The KPSS test is applied as a further test for the presence of unit roots. In the KPSS test, the null hypothesis is the absence of unit root. As in the stock index futures markets, first order and second order integration tests are run with and without a trend, respectively. The KPSS tests are applied with the lags of 0, 3, 6, 9, 12, and 15 and the results are presented in Tables 6.3 to 6.7. For all lags, the KPSS tests reject the null hypothesis of trend stationarity and accept the null hypothesis of stationary after first difference. Therefore, for all five series, all cash and futures prices are found to be non-stationary in levels and stationary after first difference. Hence, from both KPSS and ADF tests all the commodity series tested are non-stationary in levels and stationary after first difference.

6.1.3 Ordinary Least Squares (OLS) Results.

The OLS equation 4.5 (chapter 4) is used to estimate the minimum variance hedge ratios for the commodity markets. The Ordinary Least Squares (OLS) method estimates the relationship between cash and futures returns, with the hedge ratio coefficient represented by β in the equation. Given that both cash and futures returns for all markets are stationary, OLS regression between the cash and futures returns is econometrically sound. Table 6.8 presents the OLS results. The closer the β is to one the closer the hedge ratio is to being perfect[3]. From Table 6.8, the O2 and Aluminum demonstrate a close to perfect relationship between cash and futures returns, while the hedge ratios of O1, O3 and Cocoa are less than unity. Cocoa has the lowest hedge ratio estimated at a value of 0.5840 and Aluminium has the highest hedge ratio at 1.0798.

In Table 6.8, the coefficients of adjusted R^2 are relatively high in most cases except for the Cocoa series. High adjusted R^2 indicates the strength of the relationship between the spot and futures markets. The Durbin Watson (DW) is found to be more than 2 in most cases indicating the possibility of negative autocorrelation. In the cases of O2 and Aluminum, DW is near 2 which may indicate the lack of serial correlation. As in chapter 5, the serial correlation may occur as shocks persist over long periods of time. The negative serial correlation could affect the standard errors and t-ratio in the OLS regression but not the slope coefficient (β), hence there is no need to take corrective action in this particular case.

[3]Additional tests were carried out to investigate whether $\beta = 1$ or $\beta \neq 1$, and the results show that in all cases null hypothesis ($\beta=1$) is rejected.

6.1.4 The Bivariate GARCH(1, 1) Results.

According to Baillie and Myers (1991) traditional time-series analysis assumes that the current price is a linear function of past prices, however, the volatility of price changes is time-varying. Time-varying volatility in commodity prices leads to autocorrelation patterns in the conditional variance of price innovations, where the variance is conditional on an information set available at the time forecasts are being formed. As in the case of stock markets, GARCH model is applied to create time-varying hedge ratios[4].

In Table 6.9, a significant ARCH process is found in all cash and futures series. The cash (A_{11}) and futures (A_{33}) ARCH parameters are significant and less than one for all the commodity series, indicating that volatility clustering exists and the shocks to the conditional variance are not explosive. The higher the ARCH parameters the higher the volatility. The ARCH parameters for the cash series range from 0.03389 in the case of Cocoa to 0.162 in the case of Aluminium. The lowest ARCH parameter in the futures series is 0.05335 in Cocoa and the highest is 0.163 again in Aluminium. The coefficients of GARCH (B_{11} ,B_{33}) are positive and significant in all cases, indicating the impact of past variance in the cash and futures markets, respectively. From Table 6.9, the persistence measure ($A_{11} + B_{11}$, $A_{33} + B_{33}$) indicates the impact of volatility on the stock prices. All persistence measures of cash and futures prices are significant and close to one, and ranging from 0.942 in the case of Aluminum to 0.99695 in the case of O2 for the cash markets, while the persistence of the futures markets is at its highest 0.99696 in the case of O2 while at its lowest 0.929 in the case of Aluminum in comparison. High persistence implies that shocks to volatility persist over a long period of time, while, lower persistence implies that persistence of volatility would die down after a relatively short period of time. The parameters A_{22} and B_{22} represent the covariance GARCH parameters. These parameters estimate the conditional covariance between cash and futures prices. From Table 6.9 all the covariance parameters are significant implying a strong interaction between cash and futures commodity markets. The results show a significant MA terms (θ_1 and θ_2) except for the O2 cash series, which may be due to non-synchronous trading, and may arise when prices are taken to be recorded at time interval

---

[4]See section 4.4 of chapter 4.

of one regular length when in fact they are recorded at time intervals of other irregular length. Results from Table 6.10 indicate the existence of serial correlation at less than 1% and 5% in the Cocoa cash and futures, respectively. Using Ljung-Box statistics of higher order for both Cocoa series indicates no evidence of autocorrelation. The other commodity series indicate lack of serial correlation in the standardised squared residual for the Ljung-Box statistic of order 6, implying that there is no need to encompass a higher order ARCH process.

6.1.4.1 Comparison of the Hedge Ratios.

As in chapter 5, different types of hedging methods are compared by constructing the different portfolios for each method to estimate the variances as a means of comparing their performances. As in chapter 5, the portfolios are constructed as (r^c_t - $\beta_t{}^* r^f_t$), where r^c_t is the cash returns, r^f_t is the futures returns and β_t is the estimated optimal hedge ratio[5]. The unhedged, traditional and the minimum variance hedge ratios are compared to the time-varying hedge in order to analyse hedging effectiveness.

Table 6.11 reports the variances of all the methods involved, taking into consideration that the smaller the variance the more effective is the hedge ratio. The comparison in Table 6.11 is conducted only between the constant methods and the time-varying method estimated by the standard GARCH model. The reduction of variances of the portfolio using the standard GARCH model compared to the unhedged method in all cases are quite considerable. The reduction ranges from 28.66% to 92.63% in Cocoa and Aluminum, respectively. Thus, the time-varying method reduces the variance by a high percentage compared to the unhedged method. The time-varying ratio reduces the variance by 5.89%, 16.73% and 10.59% compared to the traditional methods for the Aluminium, Cocoa and O3, respectively, but it underperforms by 7.18% and 7.38% in the cases of O1 and O2, respectively. The GARCH method underperforms in all cases compared to the minimum variance method. It underperforms in the Aluminium and Cocoa cases by less than 1%. In contrast, in the stock market case from Table 5.15 part B, the GARCH method

[5]See section 5.1.4.1 of chapter 5.

outperforms the minimum variance hedge ratio in most cases.

The daily constructing of portfolios by the standard bivariate GARCH method may be too costly if the reduction in variance is small. The transaction cost may be too expensive for frequent constructing of the portfolios to implement a time-varying hedge ratio. Transactions costs may include commission, adverse price movement, the opportunity cost for variation margin, the bid-ask spread, and taxes. Costs may be also associated by the cost of management and monitoring of the hedge position, specification risk and basic risk. Given that, the investor should hedge with the appropriate hedging method using the percentage change in variance. From Table 6.11 the portfolio manager who hedges using the time-varying method by reconstructing the portfolios on a daily basis may find that this is not worth the trade off with the transactions cost in comparison to the minimum variance hedge ratio. Further detailed evidence is presented in chapter 7. However, hedging using a time-varying strategy is clearly far better than not hedging at all.

The results contrast with Baillie and Myers (1991) results where the within-sample results indicate that GARCH hedge ratios perform best in terms of reducing the conditional variance of the portfolio return for all commodities involved. For the within-sample period in this research, hedging using time-varying strategy is clearly far better than not hedging at all, but inferior to the constant minimum variance hedge ratio in all cases and in the O1 and O2 series compared to the traditional method.

6.1.5 Cointegration Results.

6.1.5.1 Engle-Granger Method.

As in chapter 5 the Engle-Granger model is used initially to test whether the cash and futures prices are cointegrated. The following equation is used to test for the cointegration relationship:

$$S_t = \alpha + \beta F_t + \varepsilon_t$$

Where, S_t and F_t are contemporaneous log of cash and futures prices at time t; α and β are parameters; ε_t is the error term. As stated in section 4.3 of chapter 4, cointegration implies that a linear combination of two or more non-stationary variables have a long run relationship. All commodity cash price and futures price are found to be non-stationary. The Engle-Granger cointegration method for the above relationship is carried out in two steps; the first step is to run the OLS regression between the S_t and F_t, while the second step checks for unit root(s) (using the ADF test) in the error term of the above regression. Each time the results show that the error term is stationary after first difference and non-stationary in levels. From Table 6.12, the error term does not contain unit roots indicating that cash and futures prices are cointegrated in all series involved. Thus, all cash and futures commodity prices are found to have a long-run relationship. As stated earlier, short run deviations from the long run cointegrated relationship are indicated by an error-correction term. This error correction term may be applied to the GARCH model to investigate the short run deviations between the cash and futures prices.

In Table 6.12, all cointegration coefficients are found to be positive, significant and close to one[6]. The lowest (β) is found in the Cocoa case, while the highest is found to be in the O2 market for both Engle-Granger and Phillips and Hansen methods.

[6]Additional tests were carried out to investigate whether $\beta = 1$ or $\beta \neq 1$, and the results show that in all cases null hypothesis ($\beta=1$) is rejected.

6.1.5.2 Phillips and Hansen Methods (Commodity Markets).

As done for the stock market, cointegration between commodity cash and futures index is also tested by means of the Phillips and Hansen method. Again the following equation is applied.

$S_t = \alpha + \beta F_t + \varepsilon_t$.

As in the section 5.1.5.2, the log of cash and futures commodity prices are assumed to be I(1) processes. The Phillips and Hansen procedure again assumed none of the regressors has a drift. Once again the lags are applied based on Parzen lag method. After saving the residual of the relationship, the unit root test (ADF) was applied to this error term. From Table 6.12, the error term does not contain a unit root. This indicates that the cash and futures prices may deviate in the short run but in the long-run they are cointegrated. Therefore, all commodity markets involved are cointegrated. This confirms the Engle-Granger results. The coefficients estimated by Phillips and Hansen method are relatively similar to those of the Engle-Granger method, while all coefficients are significant. Thus, the error correction term may be applied in the time-varying hedging method (GARCH).

6.1.6 The Bivariate GARCH-X (1, 1) Results.

The GARCH-X first requires testing for cointegration between the cash and futures prices. As the previous section shows, the cash and futures prices are found to have a long-run equilibrium relationship which indicates they are cointegrated and from the cointegrated relationship the error correction term is then applied in the bivariate GARCH model. As Lee (1994) suggests, if the error correction term from the cointegration relationship affects the conditional mean, they may also affect conditional variance. From Table 6.13, the coefficients (A_{11}, A_{33}, B_{11} and B_{33}) of cash and futures commodity series of the GARCH-X model are positive and significant. These coefficients present the ARCH and GARCH process. The covariance GARCH-X parameters A_{22} and B_{22} examine the conditional covariance between cash and futures prices, and all positive and significant. This implies a strong interaction between cash and futures prices. The ARCH parameters A_{11} and A_{33} are significant and less than one in all series. The cash ARCH parameters range between 0.03487 and 0.1774303 in the cases of Cocoa and Aluminum, respectively. In the futures series the ARCH parameters range between 0.05235 in Cocoa and 0.177726 in the case of Aluminum This indicates that the shocks to the conditional variance are not explosive. These results are similar to the GARCH results for Aluminum and Cocoa. The GARCH effects (B_{11} and B_{33}) exist indicating the impact of past variance. The sum of parameters (A_{11} + B_{11}) and (A_{33} + B_{33}) estimates are both close to unity, showing that shocks persist in conditioning the future variance of return from the cash and futures markets. From Table 6.13 the highest persistence measure is at 0.97387 in Cocoa, while the lowest is at 0.80143 in Aluminium for the cash market. The futures markets also show high level of shock persistence indicating that shocks to volatility may persist over a long period of time.

Notably, Table 6.13 shows that most of the error correction terms are positive and significant. All the parameters D_{11} and D_{33} are positive and significant implying that the impact of shock returns increases as the deviations between the cash and futures prices get larger. The D_{33} parameters take into consideration the effect of the short-run deviations on the conditional variance of the futures return, while the D_{22} parameters measures the effects of the short-run deviation on the conditional covariance. The parameters D_{22} are positive and significant in most cases except in the case of O1, where the covariance between the cash and futures prices is significantly negative and its effect reduces the volatility. Further, the D_{22} parameter is positive and insignificant for the Cocoa series. The bivariate GARCH model provides a good description of the autocorrelation and conditional heteroscedasticity characterising these commodity price series.

Table 6.14 presents the Ljung-box statistics of GARCH-X of the sixth order. Similar to the GARCH results, these indicate no serial correlation in most of commodity markets involved except in the case of Cocoa where there is evidence of serial correlation at less than 1% and 5% in the cash and futures markets, respectively. However, using Ljung-box of higher order indicates no evidence of autocorrelation. Lack of serial correlation in the standardised squared residuals implies that there is no need to encompass a higher ARCH process.

6.1.6.1 Comparison of the Hedge Ratios.

Table 6.15 presents the comparison of the different measures of hedge effectiveness. The table reports the values of each of the five measures across the five commodity series. The results indicate whether the GARCH-X methods outperforms the conventional methods and the standard GARCH methods. In the case of Aluminium, the reduction in variance by the GARCH-X model is positive in comparison to all the other methods. This implies that the GARCH-X method outperforms the other methods. For O1 the GARCH-X methods outperforms the unhedged method by 51.86%, but underperforms in comparison to the traditional, minimum variance and the GARCH method by 8.38%, 12.07% and 1.11%, respectively. The GARCH-X method only underperforms by less than 1% in the Cocoa case in comparison to the minimum variance method, while it shows exactly an identical performance as the standard GARCH method in the same series. For the O3 case the GARCH-X method outperforms all methods except the minimum variance hedge method. From Table 5.20 in the stock market analysis, the GARCH-X model performs favourably compared to the minimum variance hedge ratio in comparison to its performance for the commodity markets. Investors may find it worthwhile to choose the bivariate GARCH-X model as a hedging strategy by constructing and daily re-balancing portfolios for the all cases rather than remaining unhedged. However, they may opt for the constant minimum variance hedge strategy overall due to the high transaction cost involving with the time-varying methods. Hence, portfolio managers may hedge using the time-varying methods for the stock markets, but use the minimum variance hedge methods for the commodity markets.

6.1.7 Different Patterns Across Commodity Markets.

Figures 6.1 to 6.6 depict the constant minimum variance hedge ratio against the time-varying hedge ratios. The variation of time-varying hedge ratios propagate around the constant hedge ratio in each case. Aluminum, Brent Crude and West Texas time-varying hedge ratios are observed to cluster around the constant hedge ratio. The graphs indicate large divergence between the constant hedge ratio and the time-varying GARCH-X hedge ratio in some cases. This may be a side effect of large volume trading of the commodities markets under study which occurred as a results of both prices and quantity dimensions.

The variations in the energy markets may be a reflection to the Kuwaiti crisis and the second Gulf war and its effect which led the oil crude prices to rise dramatically in the early part of the 1990s. According to Boettcher, Merholz, and Roesler (2001) this increase of oil crude prices also reflect the increase in demand which left the oil futures market more volatile in response to the un-stability of the Gulf region during the 1990s. The volatility in commodity markets represents risk to both producers and consumers of commodities. The cluster of volatility is apparent in Aluminium series in the early and latter part of the 1990s. This may be noticed in Table 6.16 since despite the Aluminium market being more volatile in the early part of the 1990s, hedge ratio variance is lower for the Aluminium market than for the other markets studied. Meanwhile, the range for Aluminium is high at 2.16281 compared to Cocoa, O2 and O3. From Table 6.16, the minimum value of the hedge ratio is 0.000016 in Cocoa and the maximum value is 2.22128 in the O1 market. Again from Table 6.16, the O3 is noted to have a higher variance than the Aluminium and the other series.

Table 6.17 presents summary statistics from applying the GARCH-X model. The smallest variance is in the Aluminium series and the largest is in O3. Meanwhile the minimum hedge ratio is seen to be -0.34909 in the O1 series and the maximum at 1.84530 in the Aluminium. The range is estimated between 1.06625 and 1.79978 in Cocoa and Aluminium series, respectively.

The hedge ratios of the minimum variance for the commodity markets under study (Table 6.8) are estimated at 1.07975 for Aluminium, 0.58400 for Cocoa, 0.8598 for O1, 1.0173 for O2, and 0.7745 for O3. These ratios are relatively higher than the values of the constant hedge ratios estimated in different assets such as the research done by Baillie and Myers (1991). According to Baillie and Myers (1991) the constant hedge ratios are valued at 0.07 for beef, 0.25 for coffee, 0.61 for corn, 0.38 for cotton, 0.50 for gold, and 0.76 for soybeans. Inconsistency appeared in each case as the variation of time-varying hedge ratios propagate around the constant minimum variance hedge ratios.

Table 6.1

Basic Statistics For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Commodity	Variance	Skewness	Kurtosis
Cash Returns			
O1	0.000752	-1.9487[a]	38.5592[a]
O2	0.000604	-1.9535[a]	40.0227[a]
O3	0.000519	-1.7401[a]	33.0934[a]
Aluminium	0.000146	-0.0153	5.02004[a]
Cocoa	0.0003	0.27407[a]	3.96537[a]
Futures Returns			
O1	0.00058	-1.8317[a]	34.7638[a]
O2	0.000514	-2.22541[a]	40.0864[a]
O3	0.000549	-2.3340[a]	39.8364[a]
Aluminium	0.000116	0.13249[a]	4.18126[a]
Cocoa	0.000255	0.22209[a]	3.27519[a]

Notes:

a, b & c imply significance at 1%, 5% & 10% level, respectively.

Table 6.2

ADF Unit Roots Tests For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Commodity	Trend- First Order Integration		No Trend- Second Oder Integration	
	Cash Price	Futures Prices	Cash Return	Futures Return
O1	-0.00427 (-2.416)/{21}	-0.00401 (-2.2078)/{21}	-0.97362[a] (-11.105)/{21}	-1.01090[a] (-10.694)/{21}
O2	-0.00431 (-2.372)/{6}	-0.003819 (-2.1389)/{9}	-1.0468[a] (-20.8373)/{6}	-1.1124[a] (-17.0684)/{9}
O3	-0.00427 (-2.416){21}	-0.004010 (-2.2078)/{21}	-0.97362[a] (-11.105)/{21}	-1.0109[a] (-10.6949)/{21}
Aluminium	-0.003537 (-2.3364){9}	-0.003057 (2.19568){6}	-0.994921[a] (-19.8425){6}	-1.006737[a] (-26.28285){3}
Cocoa	-0.002911 (-1.6768){3}	-0.002513 (-1.74354){0}	-1.220830[a] (-29.00665){3}	-0.99654702[a] (-53.38251){0}

Notes:
a, b, & c imply rejection of the null of unit roots at the 1%, 5% & 10% level, respectively.
t-tests are in the parenthesis ( )
Number of lags in brackets { }

Critical values:
No Trend - 10% (-2.57%), 5% (-2.86), 1% (-3.43).
Trend - 10% (-3.12), 5% (-3.41), 1% (-3.96).

Tables 6.3

KPSS Unit Roots Test For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	O1 Cash Price	O1 Futures Price	O1 Cash Return	O1 Futures Return
0	18.5877[a]	18.7403[a]	0.04129	0.04812
3	4.6883[a]	4.7196[a]	0.05143	0.05153
6	2.6948[a]	2.7118[a]	0.05854	0.05699
9	1.8961[a]	1.9076[a]	0.06243	0.06081
12	1.4655[a]	1.4743[a]	0.06633	0.06235
15	1.1963[a]	1.2033[a]	0.06807	0.06342

Notes:
a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.
Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 6.4

KPSS Unit Roots Test For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	O2 Cash Price	O2 Futures Price	O2 Cash Return	O2 Futures Return
0	17.32374[a]	18.83193[a]	0.04689	0.05322
3	4.35865[a]	4.73578[a]	0.04563	0.05776
6	2.50355[a]	2.71819[a]	0.04921	0.06277
9	1.76079[a]	1.91044[a]	0.0504	0.06573
12	1.36072[a]	1.47528[a]	0.04959	0.06506
15	1.11077[a]	1.20337[a]	0.0.4901	0.06416

Table 6.5

KPSS Unit Roots Test For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	O3 Cash Price	O3 Futures Price	O3 Cash Return	O3 Futures Return
0	16.46697[a]	16.72926[a]	0.11719	0.10499
3	4.14405[a]	4.21104[a]	0.11532	0.10805
6	2.38046[a]	2.41889[a]	0.12496	0.12375
9	1.67424[a]	1.70079[a]	0.12625	0.12992
12	1.29386[a]	1.31385[a]	0.12046	0.12643
15	1.05625[a]	1.07208[a]	0.11931	0.12592

Notes:
a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.

Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 6.6

KPSS Unit Roots Test For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	Al Cash Price	Al Futures Price	Al Cash Return	Al Futures Return
0	15.96342[a]	16.52747[a]	0.08223	0.08993
3	4.00843[a]	4.14725[a]	0.08659	0.09507
6	2.29845[a]	2.37686[a]	0.08488	0.09122
9	1.61445[a]	1.66879[a]	0.08339	0.08845
12	1.24622[a]	1.28762[a]	0.08092	0.08593
15	1.01616[a]	1.04947[a]	0.08017	0.0848

Table 6.7

KPSS Unit Roots Test For (1st Jan 1990 - 31st Dec 2000) Time Period Results

Lags	Trend - First Order Integration		No Trend - Second Order Integration	
	Co Cash Price	Co Futures Price	Co Cash Return	Co Futures Return
0	38.46941[a]	37.54273[a]	0.15058	0.23306
3	9.67679[a]	9.43299[a]	0.19405	0.24618
6	5.55362[a]	5.41176[a]	0.20554	0.24705
9	3.90343[a]	3.80297[a]	0.21384	0.24824
12	3.01468[a]	2.93670[a]	0.2191	0.2495
15	2.45920[a]	2.39532[a]	0.23114	0.25664

Notes:

a, b & c imply rejection of the null of stationarity at the 1%, 5%, & 10% level, respectively.

Critical values:
No trend 10% (0.347), 5% (0.463), 1% (0.739)
Trend 10% (0.119), 5% (0.146), 1% (0.216)

Table 6.8

OLS Results For (1st Jan 1990 - 31st Dec 2000) Time Period

Commodity	α	β	R^2	D.W.
O1	0.000023 (0.07072)	0.8598[a] (61.762)	0.57068	2.7199
O2	-0.000040 (-0.2582)	1.0173[a] (145.469)	0.8806	1.9149
O3	-0.0000058 (-0.02273)	0.7745[a] (70.7354)	0.63552	2.4193
Aluminium	0.0000030 (0.05076)	1.07975[a] (190.3981)	0.926661	2.182
Cocoa	-0.00003516 (-0.12896)	0.58400[a] (34.17199)	0.289099	2.70536

Notes:

t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%

Table 6.9

BGARCH Results For (1[st] January 1990 to 31[st] December 2000) Time Period

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	-0.0002272 (-1.01608)	-0.0001588 (-0.48724)	-0.00000384 (-0.01554)	-0.00003691 (-0.21326)	-0.0002422 (-1.20938)
θ_1	0.204[a] (14.25058)	-0.02311 (-1.57730)	0.115[a] (8.21789)	0.116[a] (7.75361)	0.293[a] (20.19554)
α_2	-0.0002174 (-1.08751)	-0.0002562 (-0.93513)	0.0001599 (0.64195)	-0.00003266 (-0.19947)	-0.0001671 (-0.69773)
θ_2	0.262[a] (20.69047)	0.02200 (1.49833)	0.144[a] (10.53967)	0.114[a] (7.46315)	0.128[a] (7.66643)
C_1	0.00001605[a] (15.48417)	0.00000299[a] (7.85322)	0.00001017[a] (10.57569)	0.00001245[a] (23.17584)	0.0000062[a] (7.34821)
A_{11}	0.08999[a] (18.87384)	0.04995[a] (28.70316)	0.09510[a] (20.12670)	0.162[a] (23.10425)	0.03389[a] (11.42300)
B_{11}	0.885[a] (247.56946)	0.947[a] (619.28379)	0.885[a] (172.52397)	0.780[a] (140.57173)	0.943[a] (204.05107)
C_2	0.0002279[a] (15.57181)	0.00000320[a] (7.94002)	0.00000843[a] (12.11257)	0.00001245[a] (22.81951)	0.0000052[a] (6.24038)
A_{22}	0.107[a] (21.22022)	0.05551[a] (28.50981)	0.09106[a] (24.90854)	0.162[a] (22.68044)	0.03391[a] (11.61365)
B_{22}	0.844[a] (173.22357)	0.940[a] (539.60975)	0.890[a] (253.25112)	0.774[a] (131.69513)	0.933[a] (147.23826)
C_3	0.00002656[a] (12.27906)	0.00000321[a] (7.27558)	0.00000787[a] (11.69479)	0.00001269[a] (22.08394)	0.0000077[a] (7.59640)
A_{33}	0.153[a] (23.16362)	0.06296[a] (26.48033)	0.08498[a] (21.61955)	0.163[a] (22.19424)	0.05335[a] (11.85696)
B_{33}	0.814[a] (121.69305)	0.934[a] (435.72340)	0.904[a] (273.69201)	0.766[a] (120.5348)	0.918[a] (143.04689)
L	20898.32	22697.46	21786.63	28202.05	21544.98

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 6.10

Test for Higher Order Arch Effect (GARCH)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	3.62	4.0742	6.4477	6.7937	29.1824[a]
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	3.3346	3.6836	6.5132	6.8592	10.3045[b]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals.
a and b imply significance at 1% and 5%, respectively.

Table 6.11

BGARCH Versus Conventional Methods
Within-Sample Period (1st January 1990 - 31st December 2000) BGARCH Results

Part A
Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000752	0.000604	0.000519	0.000146	0.000300
Traditional	0.000334	0.00007220	0.000217	0.000011426	0.000257
Minimum Var	0.000323	0.00007204	0.000189	0.000010688	0.000213
BGARCH	0.000358	0.00007753	0.000194	0.000010753	0.000214

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	52.39	87.16	62.62	92.63	28.66
Traditional	-7.18	-7.38	10.59	5.89	16.73
Minimum	-10.83	-7.62	-2.64	-0.60	-0.46

Table 6.12

Within-Sample Time Period Cointegration Tests Results

Commodity	Method	α	β	Method	Unit Root Tests	
					Trend	No Trend
					First Order Integration	Second Order Integration
O1	E-G P-H	-0.0163* (-4.325) -0.0166* (-4.600)	1.0055* (800.7) 1.0057* (839.3)	E-G P-H	-0.526[a] (-9.871)/{18} -0.665[a] (-11.122)/{18}	-7.229[a] (-21.872)/{18} -8.241[a] (-21.991)/{18}
O2	E-G P-H	-0.1345* (-19.891) -0.1680* (-25.907)	1.0441* (450.7) 1.0559* (478.5)	E-G P-H	-0.052[a] (-6.479){21} -0.049[a] (-6.648)/{21}	-1.621[a](-12.578)/{24} -1.581[a] (-12.957)/{24}
O3	E-G P-H	-0.0037 (-0.391) -0.0033 (-0.379)	1.0007* (538.8) 0.9995* (593.8)	E-G P-H	-0.091[a] (-5.430)/{21} -0.088[a] (-5.594)/{21}	-4.838[a] (-12.937)/{36} -4.576[a] (-11.896)/{36}
Aluminium	E-G P-H	-0.1317* (-21.272) -0.2297* (-21.579)	1.0157* (1193.0) 1.0294* (704.7)	E-G P-H	-0.052[a] (-6.088)/{12} -0.040[a] (-6.842)/{12}	-1.732[a](-15.116)/{15} -1.338[a] (-14.854)/{15}
Cocoa	E-G P-H	0.8697* (44.753) 0.8675* (44.672)	0.8847* (327.8) 0.8850* (328.1)	E-G P-H	-0.050[a] (-5.114)/{15} -0.050[a] (-5.122)/{15}	-3.254[a](-13.032){27} -3.257[a] (-13.040){27}

Notes:
***, **, * imply significant at 10%, 5%, and 1% respectively
a, b & c imply rejection of the null of unit root at 1%, 5%, & 10% level, respectively.
t-tests in the parenthesis ( )
Number of lags in brackets { }

E-G denotes the Engle and Granger method
P-H denotes the Phillips and Hansen method

Critical values:
No Trend 10% (-2.5672),5% (-2.8633), 1% (-3.4362).
Trend 10% (-3.1289), 5% (-3.4143), 1% (-3.9674).

Table 6.13

BGARCH-X Results For (1st January 1990 - 31st December 2000) Time Period.

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	-0.00001679 (-0.07085)	-0.000318 (-0.95346)	-0.00000004 (-1.6452)	0.0000235 (0.13175)	-0.0002437 (-1.20518)
θ_1	0.08336[a] (5.16778)	-0.02604 (1.66629)	0.119[a] (7.39050)	0.114553[a] (7.08595)	0.292[a] (19.95438)
α_2	-0.00007733 (-0.33054)	0.0004008 (1.44557)	0.000262 (1.0679)	0.0000367 (0.21896)	-0.0001680 (-0.70004)
θ_2	0.147[a] (9.83956)	0.01432 (0.90733)	0.153[a] (10.6262)	0.1117555[a] (6.83232)	0.129[a] (7.73916)
C_1	0.00003586[a] (21.9148)	0.0000154[a] (14.0566)	0.0000264[a] (12.6677)	0.0000277[a] (19.4783)	0.0000065[a] (7.01696)
A_{11}	0.105[a] (15.85371)	0.07837[a] (28.8658)	0.170[a] (23.4576)	0.1774303[a] (17.73591)	0.03487[a] (11.31814)
B_{11}	0.813[a] (170.832)	0.866[a] (228.513)	0.753[a] (106.415)	0.624[a] (17.73591)	0.939[a] (189.1551)
C_2	0.0000698[a] (21.6469)	0.0000158[a] (14.0127)	0.00001727[a] (12.29303)	0.0000269[a] (20.11524)	0.0000057[a] (6.00490)
A_{22}	0.122[a] (18.8709)	0.08938[a] (30.9182)	0.134[a] (25.374)	0.1768262[a] (17.49776)	0.03555[a] (11.51132)
B_{22}	0.674[a] (112.323)	0.850[a] (222.823)	0.805[a] (173.601)	0.6183995[a] (44.83402)	0.926[a] (129.4284)
C_3	0.0000672[a] (16.3899)	0.0000148[a] (12.8232)	0.0000123[a] (11.2368)	0.0000265[a] (20.23773)	0.0000076[a] (7.16499)
A_{33}	0.149[a] (11.3908)	0.103[a] (28.8333)	0.112[a] (21.2368)	0.177726[a] (17.16427)	0.05235[a] (11.60285)
B_{33}	0.698[a] (62.3734)	0.844[a] (193.565)	0.856[a] (218.508)	0.618399[a] (44.83402)	0.914[a] (133.8071)
D_{11}	0.06846[a] (12.5117)	0.02179[a] (8.08779)	0.02619[a] (7.12246)	0.03023[a] (3.63813)	0.0005820 (1.90692)
D_{22}	-0.01462[a] (-2.8143)	0.01673[a] (6.79159)	0.01760[a] (6.07964)	0.0174185[a] (2.45176)	0.0004666 (1.30134)
D_{33}	0.02626[a] (4.8893)	0.01518[a] (6.27003)	0.01464[a] (5.9295)	0.013894[a] (2.20927)	0.001513[a] (3.63813)
L	20812.11	22598.07	21725.8	28300.51	21552.88

Table 6.14

Test for Higher Order Arch Effect (GARCH-X)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	2.011	4.0627	6.8083	3.5562	28.8571[a]
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	3.6985	1.1113	4.2107	4.3771	9.1371[b]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals.
a and b imply significance at 1% and 5%, respectively.

Table 6.15

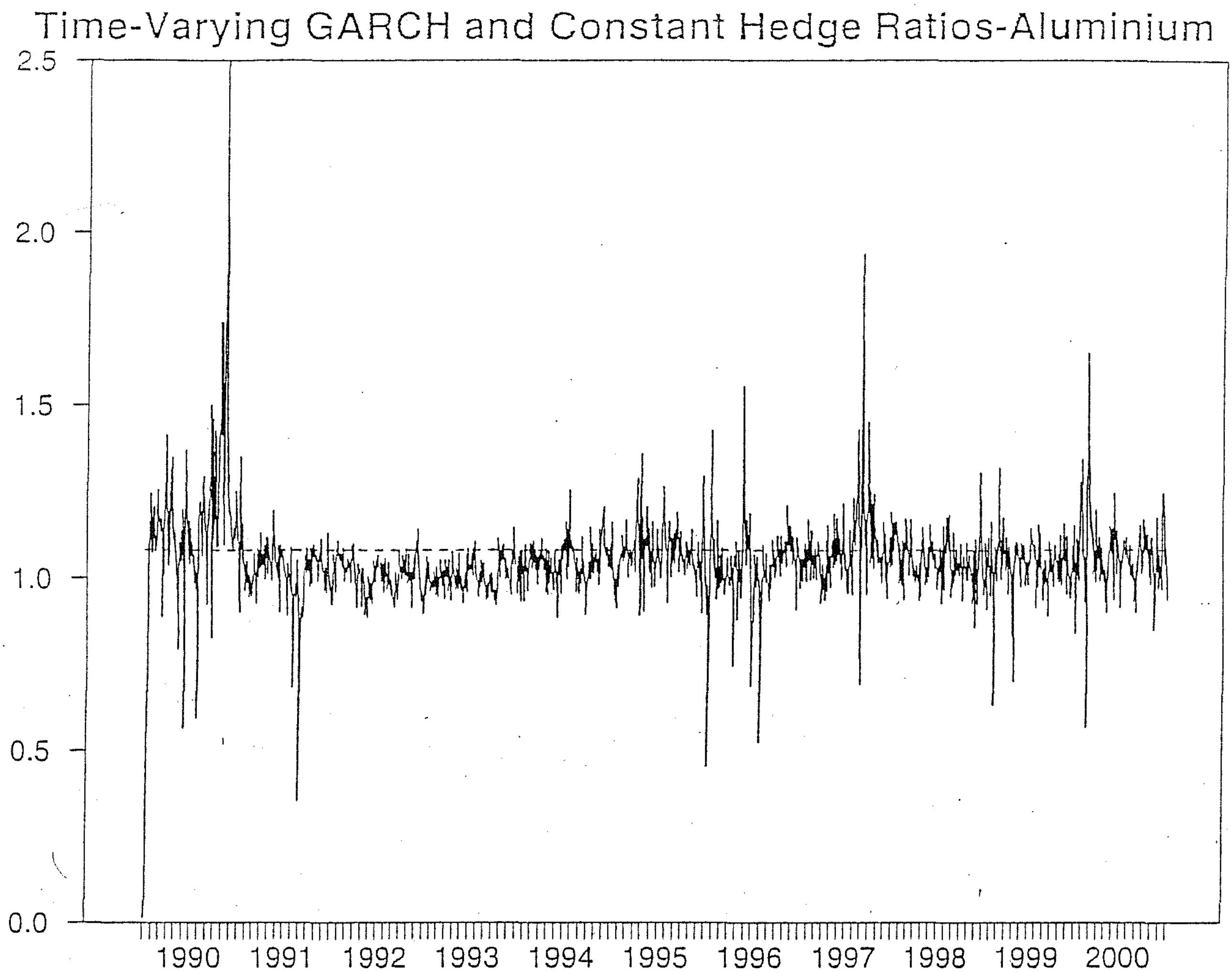
BGARCHX Versus BGARCH and Conventional Methods
Within-Sample Period (1st January 1990- 31st December 2000) BGARCHX Results

Part A
Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000752	0.000604	0.000519	0.000146	0.000300
Traditional	0.000334	0.00007220	0.000217	0.000011426	0.000257
Minimum Var	0.000323	0.00007204	0.000189	0.000010688	0.000213
BGARCH	0.000358	0.00007753	0.000194	0.000010753	0.000214
BGARCHX	0.000362	0.000078	0.000192	0.000010273	0.000214

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	51.86	87.08	63.00	92.96	28.66
Traditional	-8.38	-8.03	11.52	10.09	16.73
Minimum	-12.07	-8.27	-1.58	3.88	-0.46
BGARCH	-1.11	-0.60	1.03	4.46	0.00


Time-Varying GARCH and Constant Hedge Ratios-Aluminium
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

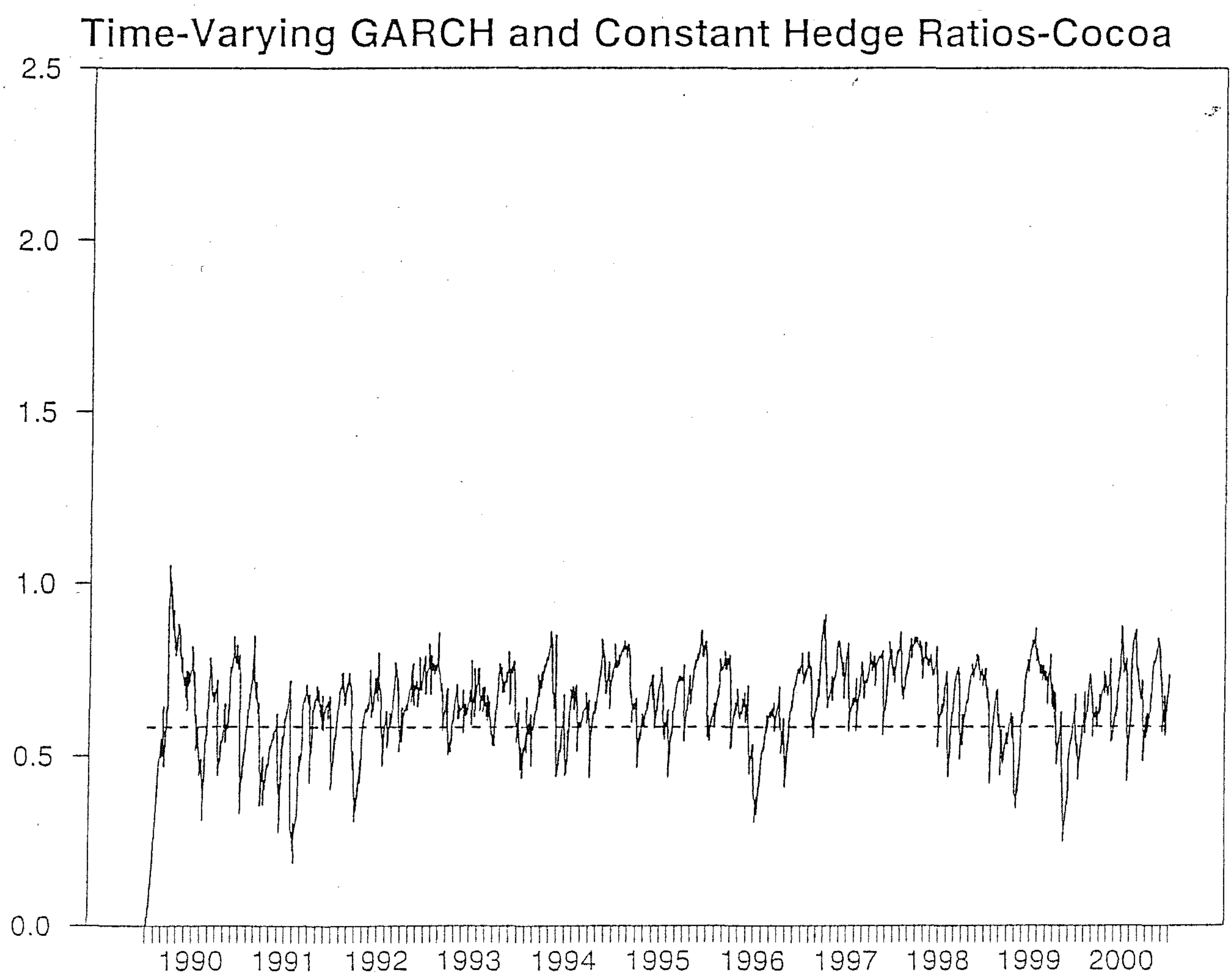
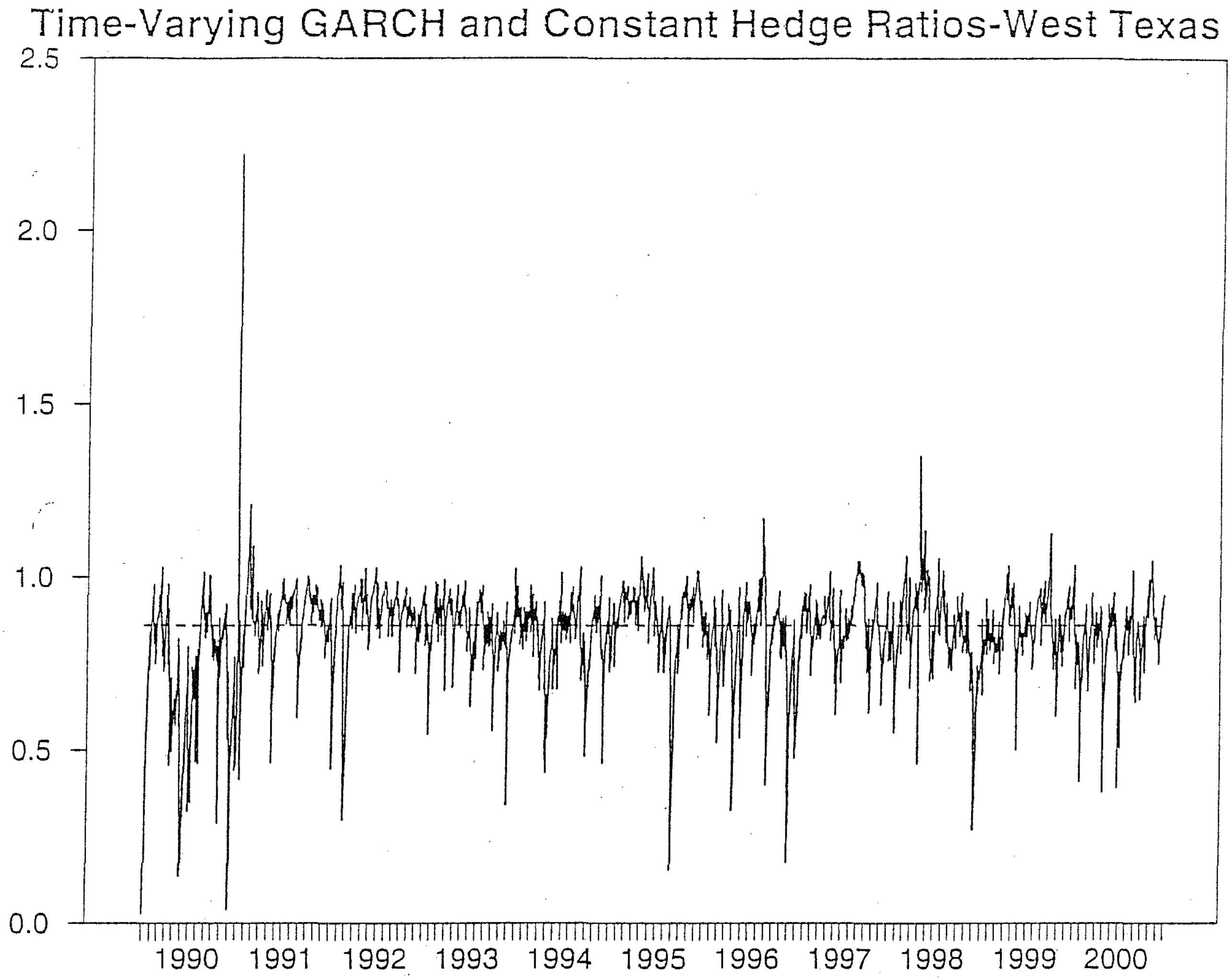

Time-Varying GARCH and Constant Hedge Ratios-Cocoa
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

Figure 6.1


Time-Varying GARCH and Constant Hedge Ratios-West Texas
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

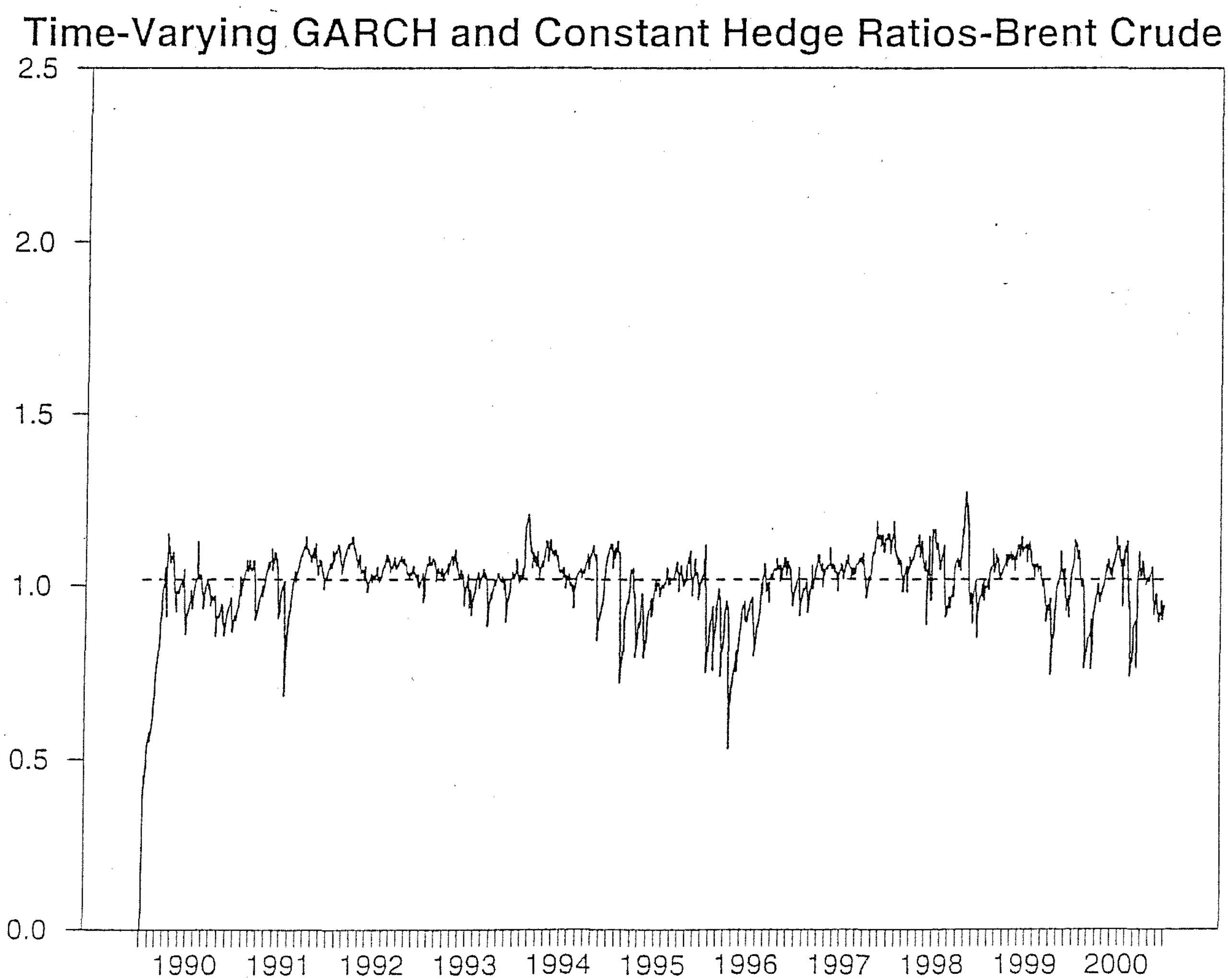

Time-Varying GARCH and Constant Hedge Ratios-Brent Crude
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

Figure 6.2

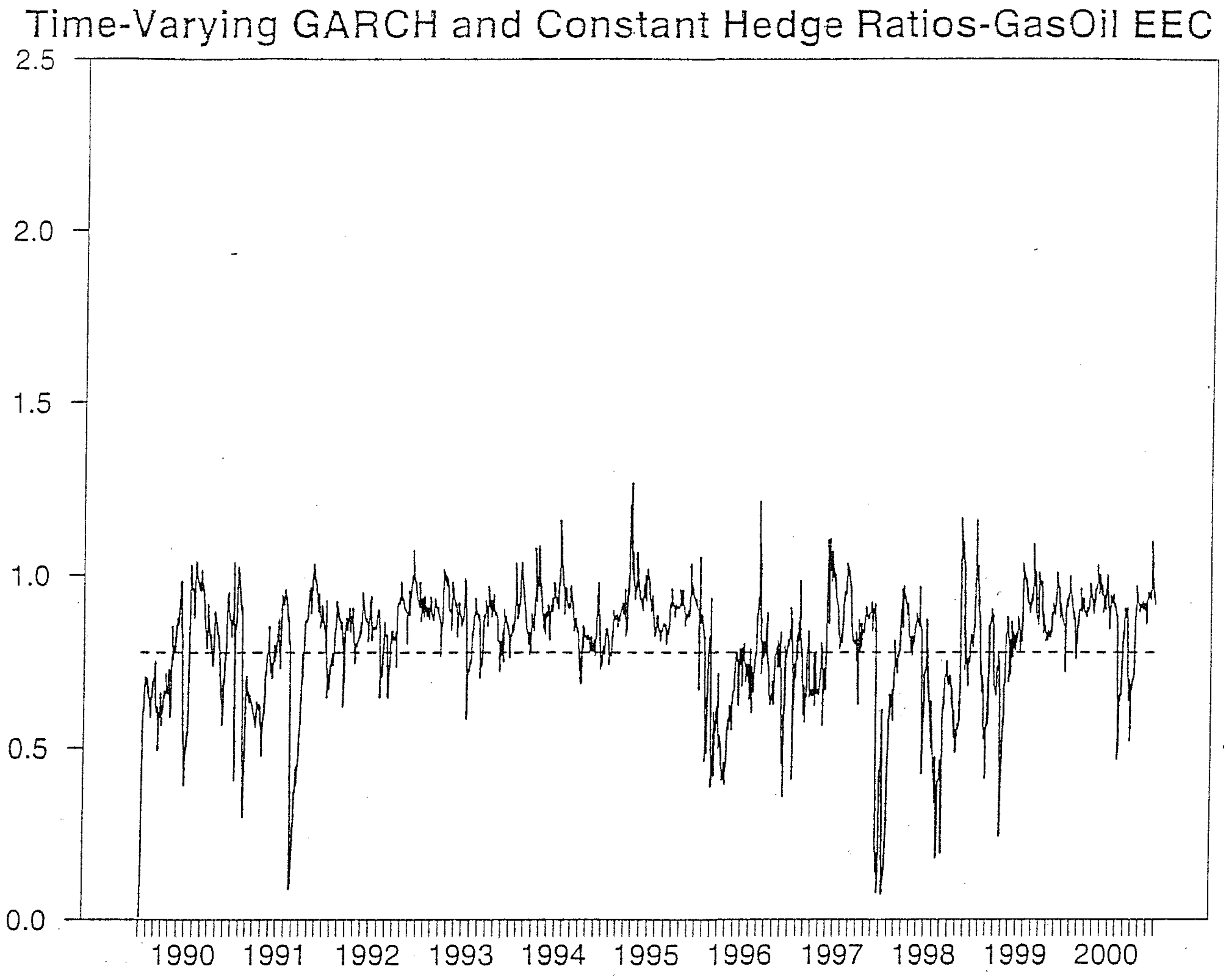
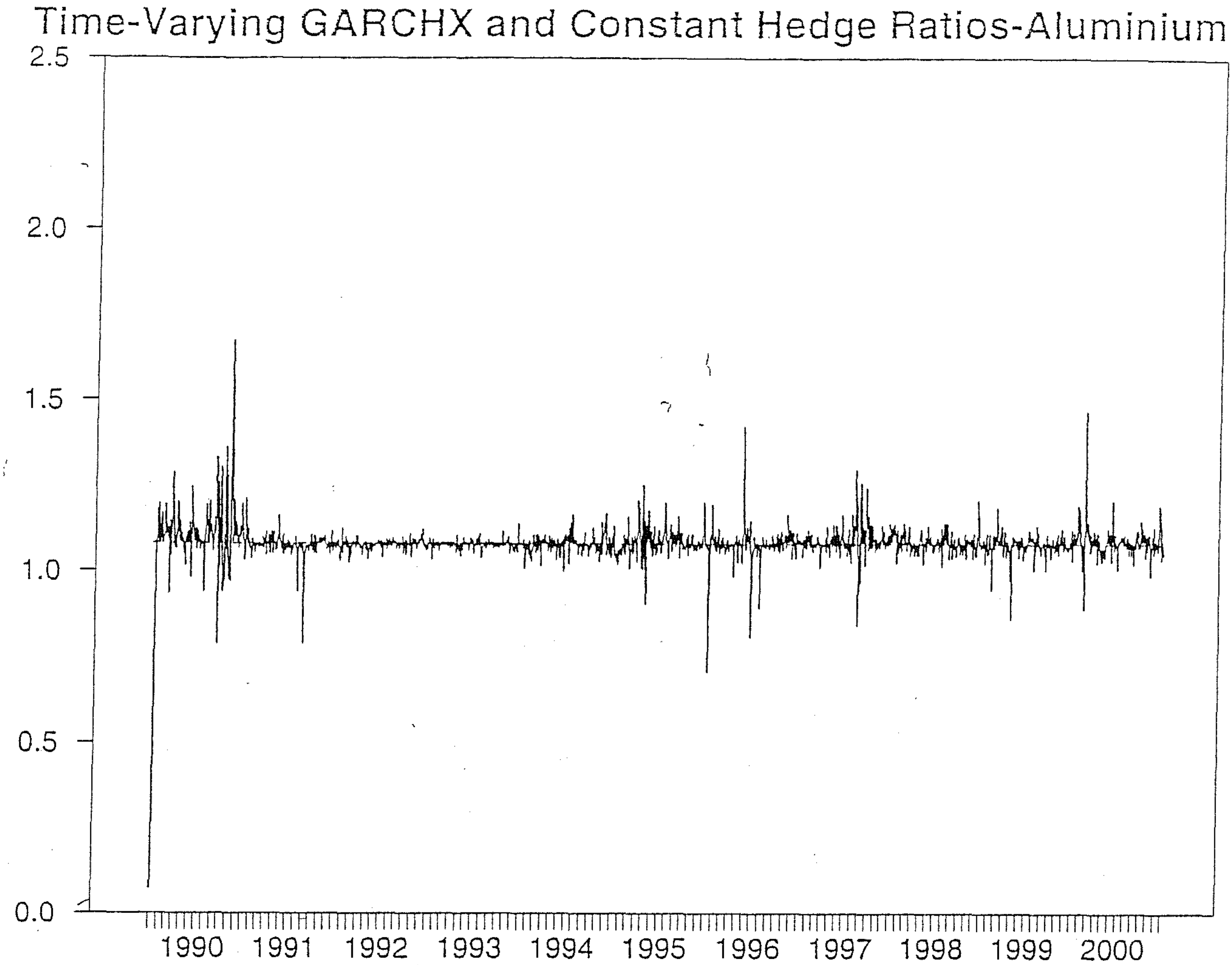

Time-Varying GARCH and Constant Hedge Ratios-GasOil EEC
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

Figure 6.3


Time-Varying GARCHX and Constant Hedge Ratios-Aluminium
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

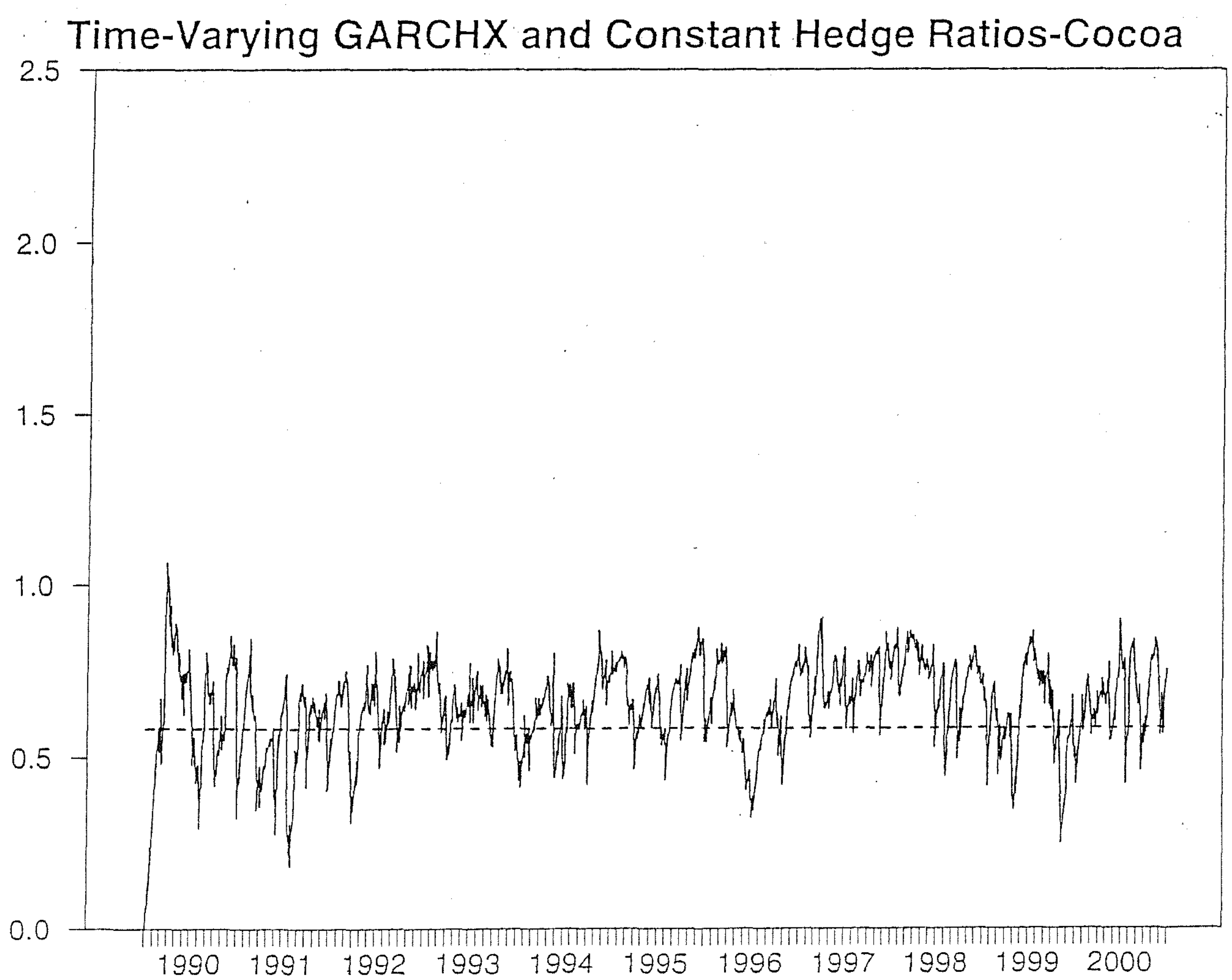
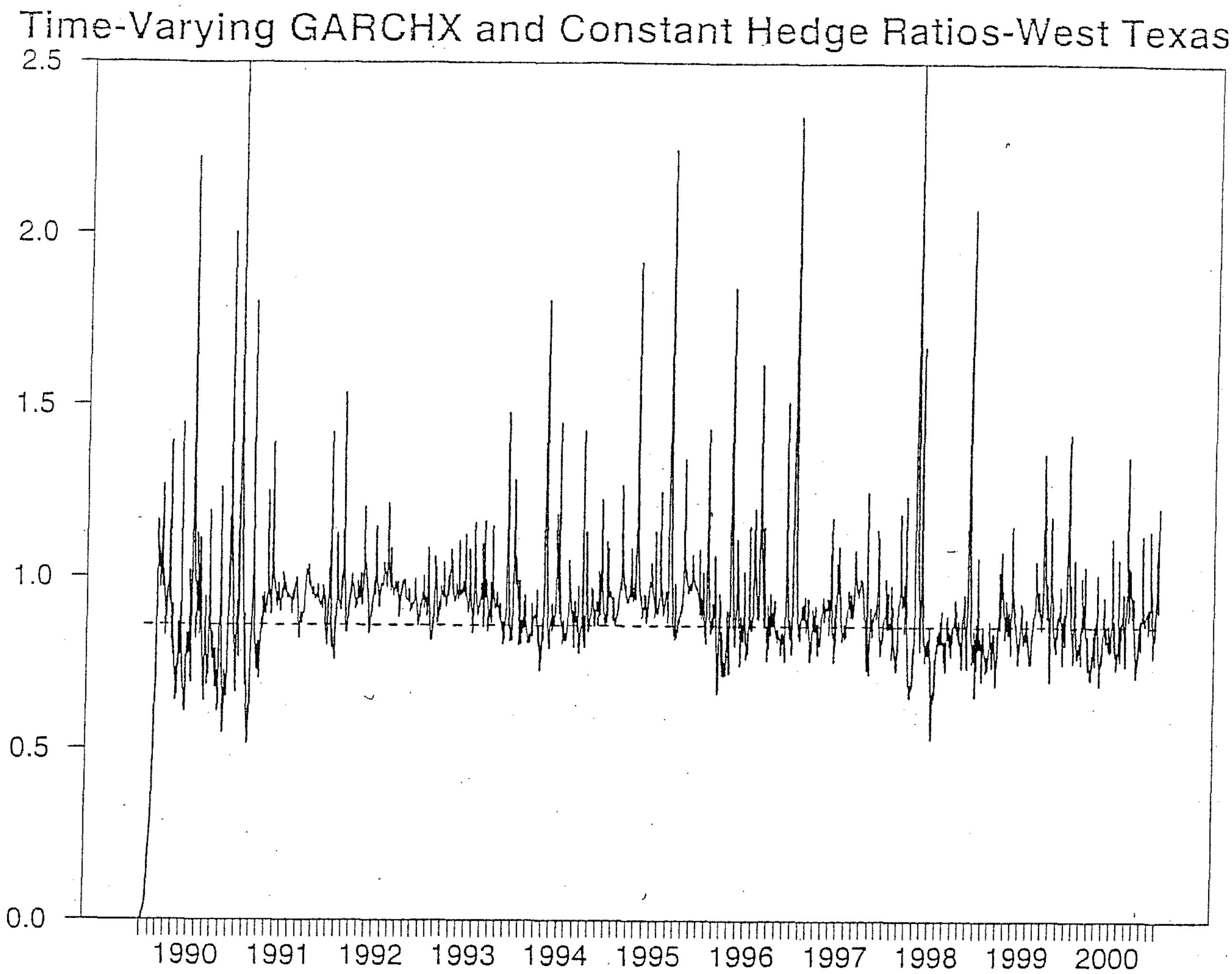

Time-Varying GARCHX and Constant Hedge Ratios-Cocoa
2.5
2.0
1.5
1.0
0.5
0.0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

Figure 6.4


Time-Varying GARCHX and Constant Hedge Ratios-West Texas
2.5
2.0
1.5
1.0
0.5
0.0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000

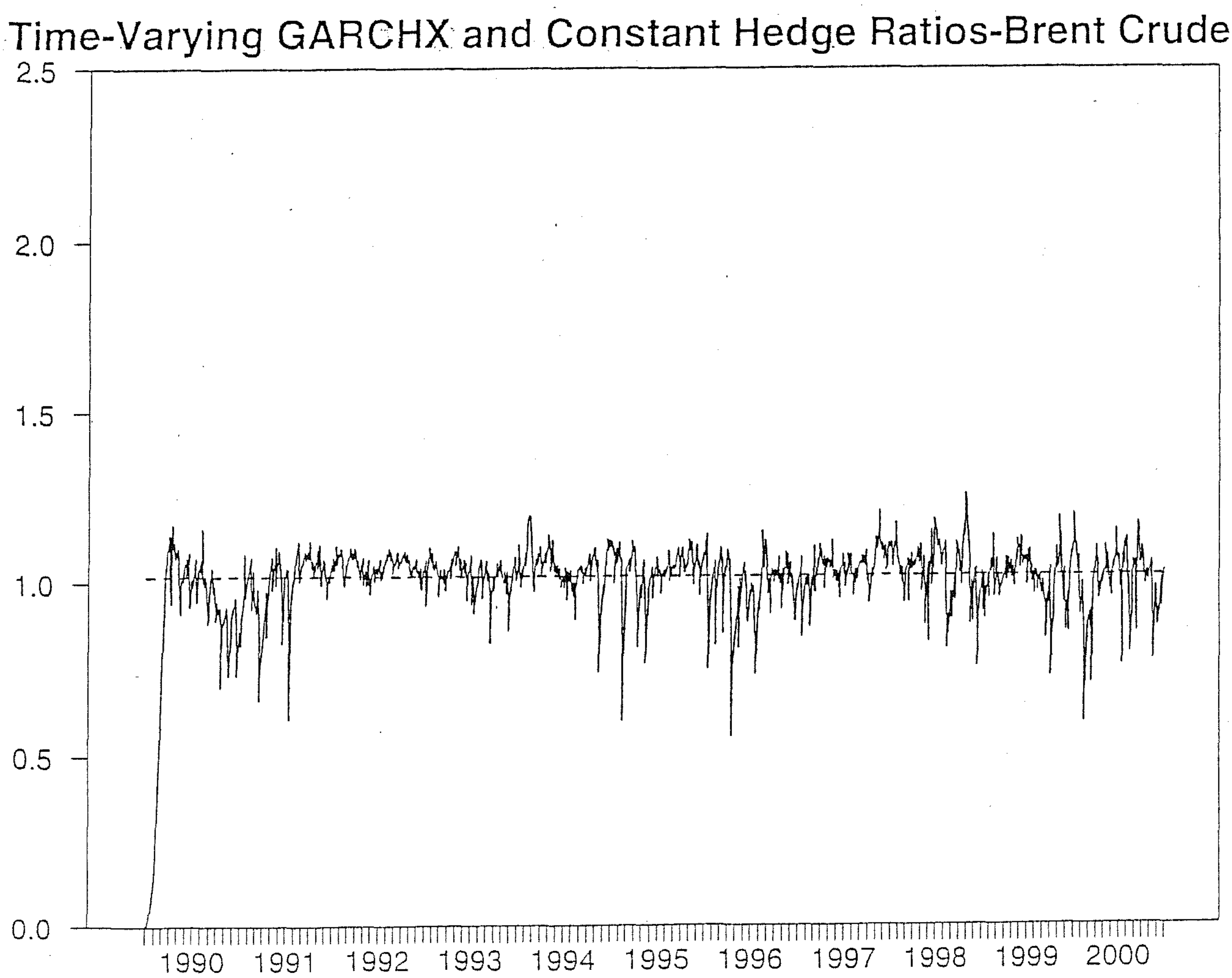

Time-Varying GARCHX and Constant Hedge Ratios-Brent Crude
2.5
2.0
1.5
1.0
0.5
0.0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000

Figure 6.5

Time-Varying GARCHX and Constant Hedge Ratios-GasOil EEC

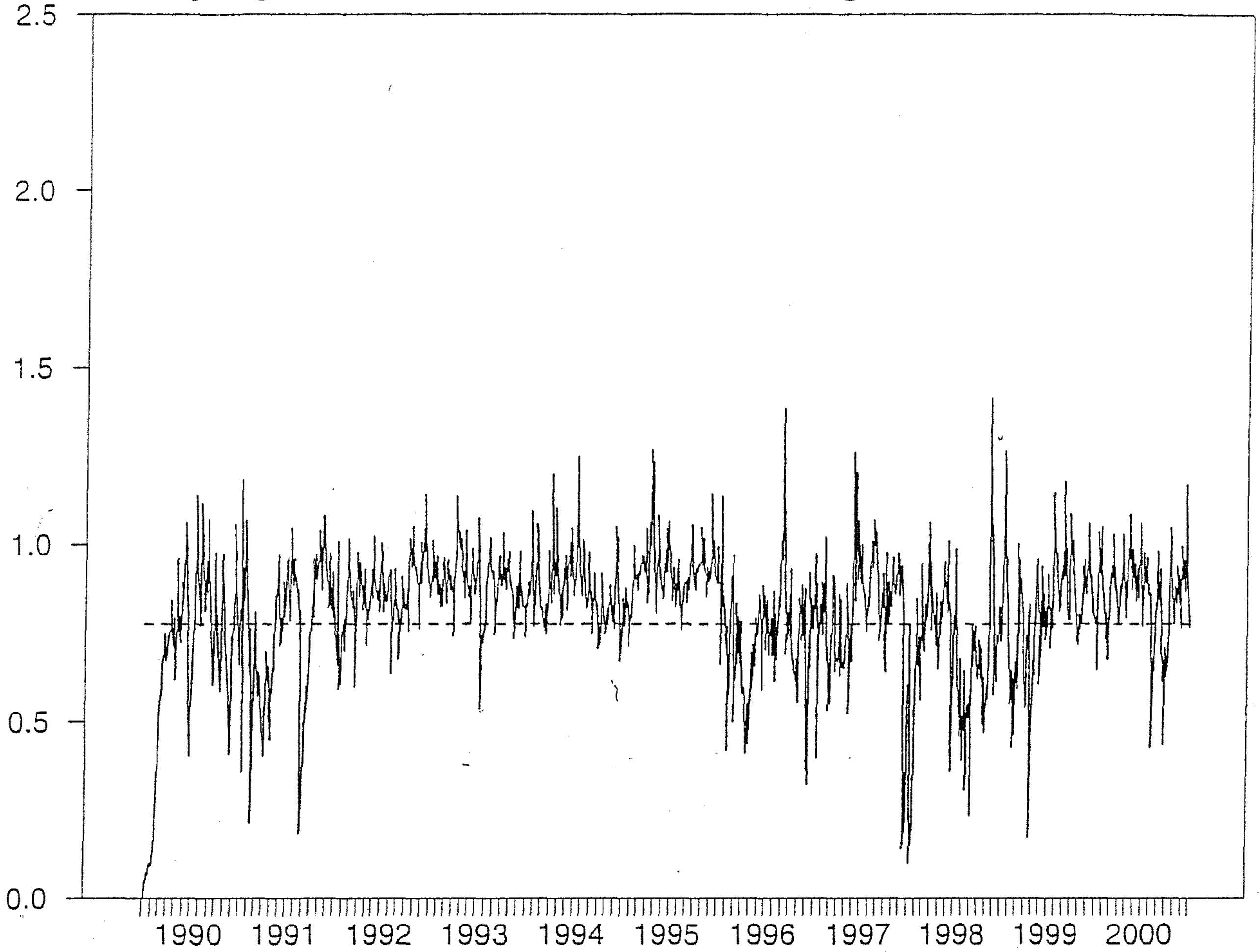


Figure 6.6

Table 6.16

Summary Statistics for Commodity Futures Markets (GARCH Model Hedge Ratios)

Markets	Obs	Mean	Std Error	Variance	Min	Max	Range
Al	2870	1.05378	0.09341	0.00872	0.01598	2.17879	2.16281
Cocoa	2870	0.64666	0.12758	0.01627	0.000016	1.05045	1.05044
O1	2870	0.83671	0.13952	0.01946	0.0271	2.22128	2.19418
O2	2870	1.00701	0.10429	0.01087	0.00342	1.26928	1.26586
O3	2870	0.80501	0.16769	0.02812	0.00916	1.26698	1.25782

Table 6.17

Summary Statistics for Commodity Futures Markets (GARCH-X Model Hedge Ratios)

Markets	Obs	Mean	Std Error	Variance	Min	Max	Range
Al	2870	1.05377	0.07349	0.0054	0.04552	1.8453	1.79978
Cocoa	2870	0.64764	0.12943	0.01675	0.00029	1.06654	1.06625
O1	2870	0.79145	0.16644	0.0277	-0.34909	1.14325	1.49234
O2	2870	1.00309	0.12671	0.01605	0.00046	1.25505	1.25459
O3	2870	0.80657	0.17995	0.03238	0.00033	1.41758	1.41725

6.2 TWO OUT-OF-SAMPLE TIME PERIODS RESULTS.

6.2.1 One Year Out-of-Sample Time Period (1st Jan 2000 to 31st Dec 2000).

Park and Switzer (1995) and Baillie and Myers (1991) claim that a more reliable measure of hedging effectiveness can be obtained from the hedging performance of different methods for out-of-sample time periods. The one year out-of-sample time period selected is from 1st January 2000 through to 31st December 2000. Price levels and returns for 1st January 1990 to 31st December 1999 were tested for unit roots and cointegration. As for the within-sample case, both ADF and KPSS tests are applied to test for the unit roots. The ADF test indicated that all commodity cash and futures series under examination are non-stationary in levels and stationary after first difference. Meanwhile, the KPSS model, which tests for the null hypothesis of stationarity against the alternative of a unit root and confirms the ADF results where all prices are non-stationary in levels and stationary after first difference. The unit root results for the out-of-sample time period are not presented in the interests of brevity but are available on request.

Similar to the stock markets in chapter 5, in order to investigate the one year out-of-sample hedging effectiveness of the five methods, the bivariate GARCH-X, GARCH models and the minimum variance equation is estimated for the period 1st January 1990 to 31st December 1999 and then the estimated parameters are applied to compute the hedge ratios and the portfolios for this out-of-sample period (1st January 2000 to 31st December 2000). Hedging effectiveness is analysed by comparing the variance of these portfolios and the percentage change in variance. This percentage change in variance is calculated as $(Var_{other} - Var_{GARCH})/Var_{others}$.

The Ordinary Least Squares (OLS) constant hedge ratios for the period 1st January 1990 to 31st December 1999 are presented in Table 6.18. All coefficients (β) are positive and significant. Again tests were carried out to investigate whether $\beta = 1$ or $\beta \neq 1$, the results show that in all cases null hypothesis are rejected. The closer the adjusted R^2 is to unity the stronger the correlation between the cash and futures prices. However, as Lindahl (1989) suggested, higher adjusted R^2s are not always consistent with lower hedging risk and greater hedging effectiveness.

Cointegration tests using the Engle-Granger method are employed to check for the presence of a long-run cointegration relationship between cash and futures prices for the five commodity futures. The two price series were found to have a long-run equilibrium relationship. Subsequently, the error correction term for the cointegration relationship is applied in the standard GARCH-X model in order to be used to estimate the time-varying hedge ratio. The standard GARCH results are presented in Table 6.19. The ARCH parameters are significant and less than unity indicating volatility clustering in the markets under study. The covariance parameters of the GARCH model indicate a significant and positive interaction between the cash and futures prices. Using Ljung-Box statistics of order 6, in Table 6.20 the standardised squared residuals show serial correlation at less than 1% and 5% for the cash and futures Cocoa series, respectively. No serial correlation is found in the other series.

Table 6.21 presents the GARCH-X results and Table 6.22 presents the Ljung-Box statistics of order 6 from the GARCH-X tests. This indicates that serial correlation exists only at less 1% for Cocoa cash, while it exists in West Texas Intermediate (O1) futures at less than 1%. No serial correlation exists in the other commodity markets under study. Lack of serial correlation in the standard squared residuals at high order using Ljung-Box implies no need to encompass a higher order ARCH process.

6.2.1.1 Comparison of the Hedge Ratios (1st Jan 2000 to 31st Dec 2000).

This section reviews the hedging effectiveness of several methods for estimating the optimal hedge ratio using different techniques of conventional and time-varying hedge ratio methods. The comparisons between the effectiveness of different hedge ratios for the out-of-sample time period are carried out by constructing portfolios and then comparing the variance of these portfolios [7]. The effectiveness of the methods are analysed by comparing the variance of the constructed portfolios, where the smaller the variance the better the hedge methods. Table 6.23 shows the GARCH hedge ratio against the constant hedge ratio methods. The risk reduction is substantial

[7] See section 5.2.1 of chapter 5.

when hedging using the GARCH method compared to the unhedged method. This reduction ranges between 32.40% in Cocoa to 94.57% in Aluminium. The GARCH model performs better than the traditional hedge method in the cases of Aluminium, Cocoa and Gas Oil EEC (O3), but underperforms in the other cases. The constant minimum hedge ratio outperforms the standard GARCH method in all but the O3 case, where the reduction in risk using the time-varying method is 18.30%. The percentage changes in variance of the minimum variance hedge compared to the GARCH method ranges between -1.68% in Cocoa to -10.69% in Aluminium.

Table 6.24 presents the variance of each portfolio and the percentage change in variance for the one year out-of-sample time period for the bivariate GARCH-X in comparison to the standard GARCH and conventional methods. From Table 6.24, the GARCH-X model clearly outperforms an unhedged method for every case involved and outperforms the traditional methods in all cases except Brent Crude (O2). The GARCH-X is more effective than the standard GARCH in the cases of O1, Aluminium and Cocoa, while its less effective in O3 case and performs just the same as the GARCH model in the O2 series. As the minimum variance hedge method performs slightly better than the time-varying methods for the commodity markets, investors may take the minimum variance hedge as a hedging strategy to reduce risk, or as Park and Switzer (1995) suggested to take an alternative strategy which involves less frequent portfolio rebalancing, such as rebalancing only when the optimal hedge ratio changes by some fixed amount, taking in mind the high transaction costs for daily re-balancing of the portfolio(see chapter 7 for details).

From a comparison of Tables 6.23 and 5.28, the GARCH model time-varying hedge for one year out-of-sample time period of the stock markets compares much better than the same length of period for the commodity. Similarly comparing Tables 6.24 and 5.29, the GARCH-X method performs better than all conventional methods for the stock, except in the Japan case for the minimum variance method. The GARCH-X method also performs better than the GARCH method in five out of seven cases. From Table 6.24, the GARCH-X performs significantly better than the unhedged. It also outperforms the traditional method and the GARCH method in most cases except O2 and O3, respectively. However, the minimum variance hedge ratio compares favourably to the GARCH-X method for the commodity markets, while it underperforms in the stock markets for most cases (see Table 5.29).

6.2.2 Two Year Time Period (1st Jan 1999 to 31st Dec 2000).

In this section, a two year out-of-sample time period of daily data from 1st January 1999 to 31st December 2000 is used to investigate and compare the optimal hedge ratios. Parameters from 1st January 1990 to 31st December 1998 are used to create the hedge ratio for the two years out-of-sample time period. Prior to that, the Augmented Dickey-Fuller (ADF) and the KPSS tests for unit roots are applied to the spot and futures series during 1st January 1990 to 31st December 1998, in order to check for stationarity. The ADF results indicate that each series is non-stationary in levels and stationary after first difference. The KPSS results which also find that all cash and futures prices are non-stationary, but cash and futures returns are stationary. The results ADF, KPSS and cointegration for the two year out-of-sample are not presented in the interest of brevity but are available on request.

Table 6.25 presents the OLS estimation results for the minimum variance method. The estimated hedge ratio indicates that all coefficients (β) are found to be positive and significant with relatively high values of hedge ratios.

Table 6.26 presents the standard GARCH results. The ARCH parameters are positive and significant in both cash and futures markets. Table 6.27 presents the two year out-of-sample test for higher order Ljung-Box statistics for the GARCH model, which shows no serial correlation in all cases, except in the Cocoa futures series where significant serial correlation exists at less than the 5% level.

To examine cointegration between the cash and futures series, the Engle-Granger method is employed to check for the long-run equilibrium relationship between cash and futures prices. The error-correction term from the cointegration relationship represents the short-run deviations from a long-run cointegrated relationship and are applied in the GARCH-X model. The results of GARCH-X with cointegration are presented in Table 6.28. Again, the ARCH parameters are positive and significant in both cash and futures markets for the GARCH-X methods. The significance of the MA term parameters (θ_1 and θ_2) in both GARCH and GARCHX may be due to non-synchronous trading. From Table 6.28, the parameters D_{22} are positive and significant except for the Cocoa series. This shows the effect of the short-run deviations on the covariance between the two residuals. The significant positive effect indicates that the prices become more volatile as the spread between the cash and futures prices gets larger. From the Tables 6.26 and 6.28 the parameters A_{22} and B_{22} imply strong interaction between the cash and futures prices. From Table 6.29 serial correlation only exists at less than 1% in cash and futures Cocoa series and at less than 5% in O1 futures. However, there are no serial correlation for the GARCH-X tests when using Ljung-Box statistics of higher order in most cases. Therefore, there is no need to encompass a higher order ARCH process.

6.2.2.1 Comparison of the Hedge Ratios (1st Jan 1999 to 31st Dec 2000).

The bivariate GARCH-X, GARCH models and the minimum variance equation are estimated for the period 1st January 1990 to 31st December 1998 and then the estimated parameters are applied to compute the hedge ratios and the portfolios for the two years out-of-sample time period. Hedging effectiveness is analysed by comparing the variance of these portfolios and the change in variance using the following formula (Var_{other} - Var_{GARCH})/Var_{others}. Table 6.30 presents the percentage change in variance by comparing the time-varying standard GARCH to the conventional methods. The standard GARCH model performs considerably better compared to the unhedged methods, where the risk is reduced by 36.41% to 95.56% in the Cocoa and Aluminium cases, respectively. The variance reduction is more effective with GARCH for the Aluminium and less effective for Cocoa. The standard GARCH model reduces risk by 5.66% in the O3 case compared to the minimum variance method, while it reduces risk again by 1.64%, 19.21% and 4.76% compared to the traditional method in Aluminum, Cocoa and O3 cases, respectively. The GARCH model out performs the constant methods in the Cocoa and O3 markets. However, the minimum variance hedge method outperforms the time-varying GARCH method in the Aluminium, O1 and O2 markets. According to the results investors may adopt the minimum variance strategy in order to minimise transaction costs.

Table 6.31 shows the GARCH-X results of the two year out-of-sample time period. The GARCH-X compares well to the unhedged method in each case. The GARCH-X also reduces risk in comparison to the traditional method in the cases of O3, Aluminium and Cocoa, while it underperforms in the other cases. The GARCH-X underperforms by less than 5% compared to the minimum variance hedge in O1, O2 and Aluminum series, while it performs better than the minimum variance hedge by 3.77% and 0.86% in O3 and Cocoa, respectively. The GARCH-X also reduces risk slightly in comparison to the standard GARCH in the cases of the Aluminum, O1 and O2, while underperforms by less than 2% in comparison to the standard GARCH in the Cocoa and O3 markets. From comparing Tables 6.30, 6.31, 5.35 and 5.36, the time-varying methods clearly perform relatively better in the stock markets than in the commodity markets.

Given the standard GARCH and GARCH-X results in tables 6.30 and 6.31, the portfolio manager may pursue a strategy whether to reconstruct the portfolio of the cases in question or opt for one of the constant methods. The comparison between the different periods of out-of-sample and the within-sample period differs. The within-sample results indicate that GARCH hedge ratios underperforms in terms of reducing the conditional variance of the portfolio returns for all five commodity. The amount of variance reduction differs from one commodity to another. Consistent with the weak hedging performance for the commodity involved, the hedge ratios fluctuate around the constant minimum variance hedge.

Comparing the GARCH model results of the one year out-of-sample period to the two year period shows some similarity as the standard GARCH compared well to the unhedged and the traditional method. From Tables 6.23 and 6.24, the GARCH model performs better in the one year period for O3, while it performs slightly better for the O3 and Cocoa for the two years periods in comparison to the minimum variance hedge ratio. Table 6.11 shows that the GARCH method under-performs in all cases compared to the minimum variance method for the within-sample. From Tables 6.11, 6.23 and 6.30, we notice that the traditional method out-performs the GARCH in O1 and O2 series in all periods. The results from Tables 6.15, 6.24 and 6.31 are relatively similar for the GARCH-X for the within-sample and both out-of-sample time periods.

The reduction of risk exists for the time-varying methods in most cases, however this modest risk reduction may not compensate for the high transaction costs. Therefore, portfolio managers may apply time-varying methods since they perform slightly better in the out-of-sample performance evaluation. In comparison, Bailie and Myers (1991) find that for the out-of-sample case, the GARCH methods perform significantly better than the constant method for each of the different commodities they studied. The out-of-sample time-varying hedge ratio in this research study performs slightly better in some of the cases but not all.

6.3 Conclusion

In the commodity markets, the time-varying hedge methods out-perform the constant variance method for the O3 series in the one year out-of-sample time period, while the time-varying methods perform better in the two year period for the O3 and Cocoa series. These cases are selected and empirically investigated while taking the transaction costs into account in the next chapter. The aim for chapter 7 is to provide evidence on whether the reduction of risk reported in chapters 5 and 6 is sufficient to compensate for transaction costs.

Table 6.18

OLS Test Results For (1st January 1990 to 31st December 1999) Time Period

Commodity	α	β	R^2	D.W.
O1	0.000003918 (0.01096)	0.8576520[a] (57.18099)	0.556211	2.722633
O2	-0.000016648 (-0.10936)	1.0194578[a] (150.38995)	0.896607	1.919253
O3	-0.000015375 (-0.05539)	0.7624581[a] (64.56893)	0.61512	2.407965
Aluminium	-0.000004398 (-0.06738)	1.0789442[a] (178.68200)	0.924481	2.181366
Cocoa	-0.000017514 (-0.06158)	0.5737106[a] (32.13734)	0.283479	2.703177

Notes:

t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%

Table 6.19
BGARCH Results For (1st January 1990 - 31st December 1999) Time Period

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	-0.0001418 (-0.63015)	0.0001576 (-0.46819)	-0.00003178 (-0.12504)	0.000o2875 (0.16373)	0.0002564 (-1.23172)
θ_1	0.203[a] (13.46206)	-0.02550 (-1.57975)	0.110[a] (7.31119)	0.1202[a] (7.60708)	-0.290[a] (18.51488)
α_2	-0.0001001 (-0.48623)	0.0002513 (-0.87948)	0.0001642 (0.64609)	0.00003661 (0.21921)	-0.0001836 (-0.74253)
θ_2	-0.252[a] (18.17484)	0.02062 (1.27878)	0.146[a] (9.85434)	0.1174[a] (7.27304)	0.129[a] (7.29437)
C_1	0.00001398[a] (14.34401)	0.00000296[a] (7.77991)	0.00001252[a] (10.48182)	0.0000113[a] (21.67223)	0.00000650[a] (7.09412)
A_{11}	0.08815[a] (18.12594)	0.04966 (26.54780)	0.103 (19.12637)	0.1624[a] (23.04141)	0.03595[a] (11.16256)
B_{11}	0.889[a] (245.02037)	0.946[a] (574.0517)	0.870[a] (142.43537)	0.7876[a] (147.82432)	0.940[a] (184.95225)
C_2	0.00001999[a] (14.842905)	0.00000307[a] (7.82667)	0.00000982[a] (12.15188)	0.0000114[a] (21.39683)	0.00000501[a] (6.01836)
A_{22}	0.103[a] (20.36679)	0.05408[a] (26.16984)	0.09398[a] (23.40209)	0.1638[a] (22.67374)	0.03585[a] (11.41023)
B_{22}	0.850[a] (175.22197)	0.941[a] (514.04050)	0.880[a] (214.65898)	0.7806[a] (138.38167)	0.933[a] (144.7726)
C_3	0.00002334[a] (11.70634)	0.00000299[a] (7.11254)	0.00000822[a] (11.59299)	0.0000116[a] (20.79253)	0.00000831[a] (7.67972)
A_{33}	0.151[a] (22.45436)	0.05989[a] (24.393961)	0.08622[a] (19.53605)	0.1658[a] (22.22734)	0.06071[a] (12.00806)
B_{33}	0.819[a] (122.84295)	0.937[a] (423.06894)	0.901[a] (242.71034)	0.7730[a] (126.45478)	0.909[a] (133.11183)
L	19120.05	20875.58	19784.34	25673.25	19629.23

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 6.20

Test for Higher Order Arch Effect (GARCH)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	3.5549	4.9246	4.9191	4.476	15.4098[a]
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	2.824	3.3655	5.1776	5.0208	8.8708[b]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals.
a and b imply significance at 1% and 5%, respectively.

Table 6.21
BGARCH-X Results For (1st January 1990 - 31st December 1999) Time Period

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	0.000088702 (0.32985)	-0.0002754 (-0.81083)	-0.00000663 (-0.02610)	0.000106339 (0.58287)	-0.0002742 (-1.30695)
θ_1	0.10333057[a] (5.72512)	-0.03078 (-1.93993)	0.114[a] (6.75231)	0.12031610[a] (7.13042)	0.289[a] (18.01263)
α_2	0.000016353 (0.06318)	-0.0003472 (-1.22477)	0.0002680 (1.08136)	0.000121757 (0.70763)	-0.0001910 (-0.77040)
θ_2	0.15596593[a] (9.69391)	0.01179 (0.69203)	0.154[a] (10.00471)	0.11651672[a] (6.80130)	0.130[a] (7.33389)
C_1	0.00005704[a] (20.89950)	0.00001717[a] (13.61758)	0.00002870[a] (12.73624)	0.00002606[a] (19.45813)	0.0000077[a] (6.76823)
A_{11}	0.13072239[a] (19.77943)	0.08556[a] (37.68110)	0.178[a] (22.11716)	0.18181015[a] (17.46403)	0.04037[a] (10.95496)
B_{11}	0.65955445[a] (118.51657)	0.853[a] (216.06557)	0.727[a] (88.81651)	0.63381311[a] (48.27948)	0.928[a] (149.2848)
C_2	0.00004036[a] (21.04381)	0.00001774[a] (13.90294)	0.00001790[a] (12.23840)	0.00002545[a] (20.08904)	0.0000056[a] (5.63878)
A_{22}	0.08952972[a] (15.32333)	0.09985[a] (36.17424)	0.133[a] (23.41954)	0.18270590[a] (17.19690)	0.03869[a] (11.04510)
B_{22}	0.75530036[a] (136.41666)	0.834[a] (211.12391)	0.794[a] (149.13428)	0.62715975[a] (48.14566)	0.921[a] (117.7290)
C_3	0.00002595[a] (17.61878)	0.00001692[a] (13.06748)	0.00001190[a] (10.72794)	0.00002528[a] (20.17876)	0.0000080[a] (7.14076)
A_{33}	0.09019323[a] (15.10871)	0.116[a] (31.09313)	0.111[a] (19.96885)	0.18527512[a] (16.85642)	0.05957[a] (11.63476)
B_{33}	0.83399614[a] (152.99113)	0.825[a] (180.73057)	0.855[a] (201.02335)	0.61847981[a] (46.63227)	0.904[a] (123.3910)
D_{11}	0.75667945[a] (15.49423)	0.02094[a] (7.28632)	0.03248[a] (7.84721)	0.02958074[a] (3.43622)	0.001040[a] (2.60231)
D_{22}	0.228808177[a] (13.59947)	0.01653[a] (6.06828)	0.02112[a] (6.84297)	0.016061061 (2.22850)	0.0008826[a] (2.10075)
D_{33}	0.079713097[a] (12.49423)	0.01534[a] (5.42348)	0.01602[a] (6.41047)	0.01211948[a] (1.94988)	0.001977[a] (3.94544)
L	19310.77	20768.22	19737.79	25763.32	19637.05

Table 6.22

Test for Higher Order Arch Effect (GARCH-X)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	2.3311	4.1261	6.3467	2.7585	13.3286[a]
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	11.4786[a]	1.041	3.2856	4.0476	7.7169

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residuals.
a and b imply significance at 1% and 5%, respectively.

Table 6.23

BGARCH Versus Conventional Methods
Out-of-Sample (1st January 2000 - 31st December 2000) Time Period BGARCH Results

Part A
Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000763	0.000795	0.000482	0.000133	0.000358
Traditional	0.000229	0.000189	0.00006419	0.000007342	0.000261
Minimum Var	0.000219	0.000189	0.00007003	0.000006515	0.000238
BGARCH	0.000241	0.000195	0.00005721	0.000007212	0.000242

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	68.41	74.96	88.13	94.57	32.40
Traditional	-5.24	-3.17	10.87	1.77	7.27
Minimum	-10.04	-3.17	18.30	-10.69	-1.68

Table 6.24

BGARCH-X Versus BGARCH and Conventional
Out-Of-Sample (1st January 2000 - 31st December 2000) Time Period BGARCH-X Results

Part A
Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000763	0.000795	0.000482	0.000133	0.000358
Traditional	0.000229	0.000189	0.00006419	0.000007342	0.000261
Minimum Var	0.000219	0.000189	0.00007003	0.000006515	0.000238
BGARCH	0.000241	0.000195	0.00005721	0.000007212	0.000242
BGARCH-X	0.000227	0.000195	0.00006019	0.000006816	0.000241

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	70.24	75.47	87.12	94.87	32.68
Traditional	0.87	-3.17	6.23	7.16	7.66
Minimum	-3.65	-3.17	14.05	-4.62	-1.26
BGARCH	5.80	0.00	-4.95	5.49	0.41

Table 6.25

OLS (1st January 1990 to 31st December 1998) Tests Results

Commodity	α	β	R^2	D.W.
O1	-0.00002704 (-0.06919)	0.852129[a] (52.34264)	0.538515	2.729148
O2	-0.00002119 (-0.13367)	1.016101[a] (144.2789)	0.898672	1.929323
O3	-0.0001029 (-0.34617)	0.755560[a] (60.71917)	0.610961	2.382182
Aluminium	0.0000076 (0.10650)	1.082577[a] (165.5563)	0.921122	2.175342
Cocoa	0.0000480 (0.16093)	0.574425[a] (29.54542)	0.270876	2.730183

Notes:

t-statistics in parentheses.
D.W. = Durbin-Watson statistics
a, b and c imply significant at 1%, 5% and 10%

Table 6.26
BGARCH Results For (1st January 1990 - 31st December 1998) Time Period

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	-0.0006196[a] (-2.97232)	0.0004355 (-1.32920)	-0.0003372 (-1.27707)	-0.00008812 (-0.48530)	-0.00009775 (-0.42022)
θ_1	-0.170[a] (10.91449)	-0.01103 (-0.60906)	0.110[a] (6.30562)	0.130[a] (7.49228)	0.289[a] (15.21617)
α_2	-0.0005641[a] (-2.83350)	-0.5252 (-1.95600)	-0.00008604 (-0.34031)	-0.00008063 (-0.47184)	-0.0000076 (-0.02738)
θ_2	0.223[a] (15.49463)	0.03661[a] (2.05103)	0.159[a] (9.72461)	0.126[a] (7.18262)	0.9916[a] (4.74291)
C_1	0.00005883[a] (18.91446)	0.00001208[a] (12.66275)	0.00002620[a] (13.51516)	0.00001932[a] (24.00660)	0.00005491[a] (9.11809)
A_{11}	0.313[a] (32.00553)	0.101[a] (29.61898)	0.156[a] (20.13554)	0.240[a] (23.44466)	0.09937[a] (9.30258)
B_{11}	0.661[a] (105.55094)	0.879[a] (268.14318)	0.783[a] (91.50177)	0.685[a] (108.08091)	0.705[a] (28.10043)
C_2	0.00006169[a] (19.35302)	0.00001210[a] (13.23261)	0.00001871[a] (15.80582)	0.00001875[a] (24.49310)	0.00003566[a] (7.71715)
A_{22}	0.261[a] (25.26831)	0.111[a] (32.24010)	0.132 (23.55756)	0.240[a] (22.66202)	0.07452[a] (8.19472)
B_{22}	0.648[a] (89.30162)	0.866[a] (271.31378)	0.818[a] (160.90100)	0.680[a] (103.25330)	0.708[a] (22.86405)
C_3	0.000005254[a] (15.00020)	0.00001158[a] (12.43249)	0.00001386[a] (14.19464)	0.00001858[a] (24.28902)	0.00004628[a] (10.92351)
A_{33}	0.266[a] (22.64438)	0.128[a] (30.27243)	0.121[a] (20.37449)	0.241[a] (21.84626)	0.119 (9.86787)
B_{33}	0.690[a] (74.92947)	0.857[a] (235.93265)	0.859[a] (198.25184)	0.674[a] (94.42609)	0.700[a] (33.18259)
L	17116.71	18.736.01	17766.27	22983.75	17674.01

Notes:

a , b and c imply significance at the 1%, 5% and 10% level respectively.
t-test in parentheses
L = log-likelihood

Table 6.27

Test for Higher Order Arch Effect (GARCH)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	1.8583	3.0332	3.2503	3.6867	5.765
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	4.5993	1.7128	3.3679	5.4691	9.3404[b]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residual.
a and b imply significance at 1% and 5%, respectively.

Table 6.28

BGARCH-X Results For (1st January 1990 - 31st December 1998) Time Period

Parameters	O1	O2	O3	Aluminium	Cocoa
α_1	-0.0002530 (-0.94535)	-0.0004030 (-1.13351)	-0.0002414 (-0.95404)	0.00000404 (0.02125)	-0.0000520 (-0.23465)
θ_1	0.121[a] (6.44391)	-0.02400 (-1.40736)	0.115[a] (6.56689)	0.12776777[a] (7.14198)	0.294[a] (18.53114)
α_2	-0.0002786 (-1.04832)	-0.0004536 (-1.51107)	0.00004426 (0.216122)	0.00002221 (0.12399)	-0.0000155 (-0.06043)
θ_2	0.166[a] (9.93316)	0.02141 (1.26712)	0.202[a] (13.87001)	0.12314370[a] (6.74691)	0.124[a] (6.68843)
C_1	0.00005043[a] (18.90349)	0.00000422[a] (8.41421)	0.00002415[a] (11.13617)	0.00002735[a] (17.47669)	0.0000027[a] (5.43502)
A_{11}	0.138[a] (20.27310)	0.04492[a] (26.85058)	0.144[a] (17.00008)	0.18636376[a] (16.92832)	0.02034[a] (9.73063)
B_{11}	0.671[a] (112.21034)	0.939[a] (483.13289)	0.763[a] (73.91776)	0.61868458[a] (41.53512)	0.967[a] (326.2316)
C_2	0.00003594[a] (19.28817)	0.00000437[a] (8.31060)	0.00002814[a] (11.15105)	0.00002703[a] (17.71489)	0.0000039[a] (4.61102)
A_{22}	0.08965[a] (15.13051)	0.05034[a] (24.87919)	0.165[a] (16.55048)	0.18919945[a] (16.67087)	0.02463[a] (8.08164)
B_{22}	0.754[a] (134.04680)	0.932[a] (400.72879)	0.715[a] (53.02526)	0.60807785[a] (39.98076)	0.945[a] (125.6460)
C_3	0.00002335[a] (15.92310)	0.00000421[a] (7.45726)	0.00004053[a] (11.78085)	0.00002709[a] (17.58155)	0.0000077[a] (6.38010)
A_{33}	0.09271[a] (14.85085)	0.05664[a] (21.33835)	0.25[a] (18.51297)	0.19429135[a] (16.36385)	0.05099[a] (9.41723)
B_{33}	0.836[a] (149.04759)	0.927[a] (316.54047)	0.644[a] (43.38807)	0.59518098[a] (37.41644)	0.910[a] (102.7481)
D_{11}	0.690[a] (14.79890)	0.004902[a] (4.90946)	0.02603[a] (7.25057)	0.0370706[a] (3.60683)	0.0004070[a] (2.20069)
D_{22}	0.213[a] (12.81502)	0.003798[a] (3.94113)	0.02660[a] (6.41831)	0.0205703[a] (2.38067)	0.0005144 (1.80652)
D_{33}	0.07634[a] (11.79661)	0.003976[a] (3.86218)	0.04343[a] (7.25969)	0.0156374[a] (2.09051)	0.001835[a] (3.88716)
L	17365.59	18946	17774.77	23172.12	17774.57

Table 6.29

Test for Higher Order ARCH Effect (GARCH-X)

Series	Ljung-Box	O1	O2	O3	Al	Cocoa
Cash Equations						
$(\varepsilon_{1,t})^2/H_{11,t}$	Q(6)	2.1229	4.0394	5.6507	. 2.7241	19.4763[a]
Futures Equations						
$(\varepsilon_{2,}t)^2/H_{22,t}$	Q(6)	9.9045[b]	1.6091	3.9751	4.269	12.8910[a]

Notes:

Q(6) is Ljung-Box statistic of order 6.
$(\varepsilon_{i,}t)^2/H_{ij,t}$ is standardised squared residual.
a and b imply significance at 1% and 5%, respectively.

Table 6.30

BGARCH Versus Conventional Methods
Out-of-Sample (1st January 1999 - 31st December 2000) Time Period BGARCH Results

Part A

Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000635	0.000698	0.000446	0.000120	0.000357
Traditional	0.000167	0.000131	0.000105	0.000005417	0.000281
Minimum Var	0.000161	0.000131	0.000106	0.000005023	0.000231
BGARCH	0.000178	0.000137	0.000100	0.000005328	0.000227

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	71.96	80.37	77.57	95.56	36.41
Traditional	-6.58	-4.58	4.76	1.64	19.21
Minimum	-10.55	-4.58	5.66	-6.07	1.73

Table 6.31

BGARCH-X Versus BGARCH and Conventional Methods
Out-of-Sample (1st January 1999 - 31st December 2000) Time Period BGARCH-X Results

Part A
Variance of the Portfolio

Hedge Type	O1	O2	O3	Aluminium	Cocoa
unhedged	0.000635	0.000698	0.000446	0.000120	0.000357
Traditional	0.000167	0.000131	0.000105	0.000005417	0.000281
Minimum Var	0.000161	0.000131	0.000106	0.000005023	0.000231
BGARCH	0.000178	0.000137	0.000100	0.000005328	0.000227
BGARCH-X	0.000168	0.000136	0.000102	0.000005178	0.000229

Part B
Percentage Change in Variance

Hedge Type	O1	O2	O3	Aluminium	Cocoa
Unhedged	73.54	80.51	77.13	95.68	35.85
Traditional	-0.59	-3.81	2.85	4.41	18.50
Minimum	-4.34	-3.81	3.77	-3.08	0.86
BGARCH	5.61	0.72	-1.96	2.81	-0.88

CHAPTER SEVEN

7.0 EMPIRICAL INSIGHTS INTO TIME-VARYING HEDGING WITH TRANSACTIONS COSTS

7.1 Introduction.

The aim of this chapter is to identify the most practical hedging method among those applied in the previous chapters of the thesis. The metric used previously (the percentage change in variance) offers an indication of the effectiveness of the hedging strategies. However, in this chapter, the practicality of using time-varying methods is investigated in detail, including accounting for transaction costs. Such trading costs in stock index or commodity futures are much lower than for the underlying asset. The previous chapters 5 and 6 demonstrate that the daily time-varying hedge ratios fluctuate around the constant hedge ratio in most cases. An alternative strategy may be considered according to Park and Switzer (1995), who suggested less frequent re-balancing, such as re-balancing only when the optimal hedge ratio changes by at least a fixed minimum amount. This approach is proposed by Park and Switzer (1995) for future research, which is now undertaken in this chapter and regarded as a further major contribution made by the thesis. Investors can hedge a long cash position by selling futures. It is assumed that the investor takes out futures positions and reevaluates a particular portfolio on a daily basis. Each day the portfolio may be adjusted to reflect changing information and economic conditions.

In this chapter, I investigate the trade off (identified in previous chapters) between the risk reduction and transaction costs, to determine the practicality of applying the time-varying hedge methods of GARCH and GARCH-X on a daily basis for the stock and commodity futures markets under study. Previous related research stops short of investigating this trade off between risk reduction and transaction costs. The focus of this chapter is to empirically examine whether it is beneficial to rebalance the portfolio on a daily basis. Based on the percentage change in variance for the futures markets involved, we present evidence in chapters 5 and 6 comparing the performance of each type of hedge, where portfolios implied by the computed hedge ratios are constructed for each day. The variance of the constructed portfolios are calculated and compared. From chapters 5 and 6, all hedging methods reduce the variance of the cash portfolio significantly. In the stock index futures markets, the time varying hedge methods out-performed the minimum variance hedge method in most cases but not all, for the out-of-sample time period. For the commodity markets, the time-varying hedge methods frequently under-performed compared to the minimum variance hedge method. The cases where the time-varying hedge ratio methods out-perform the minimum variance hedge ratio will be investigated. The empirical investigation is conducted to determine whether the time-varying methods give an improved hedging strategy after accounting for the transaction costs, as investors are likely to re-balance portfolios using a dynamic hedging strategy only if the potential risk reduction gains from frequent re-balancing are sufficient to offset the expenses due to transaction costs.

The previous chapters 5 and 6 investigated the out-of-sample performance of time-varying hedge ratios and the percentage change in variance over the minimum variance hedge ratio for one and two year out-of-sample time periods for commodity and stock markets. As explained in section 5.1.4.1, the change in variance is calculated by $(Var_{other} - Var_{Garch})/Var_{others}$. The main theme of this chapter is to investigate the hedge efficiency of the time-varying hedge ratio by means of the GARCH and GARCH-X models in the presence of transactions costs in comparison to the constant minimum variance hedge method. Park and Switzer (1995) and Baillie and Myers (1991) support the notion that the more reliable measure of hedging effectiveness is the hedging performance of different methods for out-of-sample periods. It is important to note that the objective is to have continuous exposure to the forward price of the index, using the near contract. The portfolio manager should be on the look out for opportunities to roll over into the next contract as soon as the position is established. The ideal opportunity is to sell the near contract high and buy the far contract cheap. The portfolio manager should roll over the position in order to avoid thin markets, expiration effects and to keep cost to a minimum.

The investigation of hedging effectiveness for the out-of-sample time period is conducted between the minimum variance, GARCH and GARCH-X methods for the one year and two years out-of-sample time periods. It was noted in the previous chapters 5 and 6 that the time-varying conditional variance model improves the hedging performance in some cases for the stock index and commodities futures contracts examined. Previous studies have not demonstrated the economic viability of the time-varying hedging methods with futures markets in the presence of transaction costs. This chapter investigates this issue for the futures markets studied in chapter

5 and 6.

The cases where the time-varying methods out-performed the constant method will be investigated further in this chapter, subsequently allowing for the transaction costs. For the one-year out of sample period, in the stock index futures markets studied, the GARCH method out-performed the minimum variance method in Australia, Germany, Hong Kong, South Africa, UK and USA markets, while the GARCH-X method out-performed the minimum variance method in Australia, Germany, Japan, South Africa and the US. Meanwhile, for the two year out-of-sample period, the GARCH model out-performed the minimum variance method in the cases of Australia, Germany, Hong Kong, Japan and South Africa, while the GARCH-X out-performed the minimum variance method in Germany, Hong Kong, Japan and South Africa.

For the commodity markets, the time-varying methods of GARCH and GARCH-X out-performed the minimum variance method in the one year out-of-sample time period for the O3 market only. The same methods again out-performed the minimum variance method in the two year out-of-sample period for the O3 and Cocoa markets only. This may encourage applying time-varying hedge methods after taking into account the economic viability. For the commodity market, the Gas Oil EEC (O3) is investigated in the one year out-of-sample period and Gas Oil EEC (O3) and Cocoa markets in the two year out-of-sample time periods. Telser and Higinbotham (1977) indicated that futures contracts appear only for those commodities where the benefits outweigh the costs. They concluded that the organisation of futures markets is the response to an increase of the price variability and most importantly they noted that price variability of commodities affects the benefits and costs in futures markets.

The chapter is organised as follows. Section 7.2 discusses the related literature and section 7.3 presents the methodology applied in the empirical work. Section 7.4 discusses the summary statistics, while section 7.5 discusses the results and finally section 7.6 concludes the chapter.

7.2 Literature Review

The section reviews closely related literature and identifies the lack of previous evidence on the topic of this chapter. Park and Switzer (1995) pointed out that the shortcoming of the time-varying methods is the necessity for frequent rebalancing of the hedge portfolio to follow the changing optimal hedge ratio. The trade off between the risk reduction and transaction costs will determine the practicality of the time-varying hedging method. They suggested that an alternative strategy which involves less frequent re-balancing, such as re-balancing only when the optimal hedge ratio changes at least by some fixed minimum amount, may prove to be more effective. This suggestion by Park and Switzer (1995) was as a future research topic and this became part of the motivation for this chapter.

The literature on hedge effectiveness offers incomplete evidence on the trade off between risk reduction and transaction costs. Several research studies focussed on the trading cost of price leadership. Kim, Szakkmay and Schwarz (1999) suggested that price leadership and trading costs appear to be linked across the S&P500, NYSE and MMI Futures, but there was no mention of the practical trade off between transaction costs and risk reduction. The trading cost of price leadership indicates that the market with the lowest overall trading costs will react most quickly to new information. Again, researchers such as Gay and Jung (1999) examined the important role of transaction costs and short sales restrictions, using the cost-of-carry model and an alternative equilibrium pricing model. They pointed out that trading costs play an important role in assessing futures mis-pricing without referring to the hedge ratio practicality. Wang, Yau and Baptiste (1997) examined the relationship between trading volume and transaction costs in seven financial, agricultural and metal futures. The transaction components include transaction tax, brokerage commission, exchange and clearing fees, transfer fees and taxes.

The advantages of hedging with futures come at a cost. It is uncommon to create a perfect hedge because the cash and the futures markets may not move perfectly together, indicating an imperfect relationship between cash and futures series. This imperfect relationship may be partly due to futures contract specifications. A hedger pays transaction costs which generally reduce expected return by the amount of the transactions costs and risk involved. Transaction costs may be influenced by the size of the hedge, price and delivery date. Therefore, the trade off between risk reduction and transaction costs gives the hedger the opportunity to select a suitable hedging strategy.

Recent studies find that the time-varying conditional variance model improves the hedging performance in various futures contracts. However, there are no considerable attempts to demonstrate the economic viability of the time-varying hedge method with commodity and stock index futures in the presence of transactions costs. Many researchers and academics including Myers and Thompson (1989), Myers (1991), Baillie and Myers (1991), Castelino (1992), Cecchetti, Cumby and Figlewski (1988), Lindahl (1992), Park and Switzer (1995) and Choudhry (1999) investigated the hedging effectiveness, while making no reference to the practicality of the hedging strategy in the presence of transaction costs.

From these researchers, Myers (1991) indicated that more efficient use of available information can be achieved by updating the GARCH model's parameter estimates as each new observation becomes available. However, according to Myers (1991) this is very costly and is not attempted in his paper. Figlewski (1985) indicated the cost of hedging at a particular time is noted by looking at the return that would be earned on a hedge of the index portfolio. Meanwhile, Choudhry (1999) estimated the traditional, the minimum variance and the time-varying hedge ratios, and compared their hedging effectiveness for three Pacific-Basin futures markets. Choudhry indicated that hedging away the risk must also hedge away the expected return to bearing that risk. This was mentioned by Choudhry as an indication to the cost of hedging and the reward to risk reduction in futures market without further detailed consideration of transactions costs. Myers and Thompson (1989) developed a generalised approach to estimating optimal hedge ratios on futures markets in comparison to the performance of simple regression hedging rules which provides information on the size of economic benefits. Again, Myers and Thompson (1989) had no reference to the practicality of the generalised approach in terms of the transaction costs. Cecchetti et al (1988) indicated that only a totally risk averse investor can make an optimal hedging decision without taking the impact on both risk and return into account. They also pointed out that without referring to hedging practicality hedgers may hedge partially or selectively, and remain exposed to markets risk on part of their position or part of the time, while many potential hedgers decide that hedging is not attractive for them because it is too expensive.

Finally, Lindahl (1992) show the duration and expiration effects on the minimum variance hedge ratio for the stock index futures. Lindahl had no mention of the trade off between risk reduction and transaction costs.

Low transactions costs are regarded as one of the main reasons for the success of financial futures markets (Kling, 1986). Kling also indicated that transaction costs play a fundamental role in the economic analysis of futures markets. Concerning the transaction costs, Kling (1986) concluded that if all transaction costs were equal in cash and futures markets, there would be no portfolio reallocation that could be achieved more readily in futures markets than in cash markets. Sutcliffe (1997) indicated that the transactions costs for trading futures comprise of commission, the bid-ask spread, market impact, initial margin, and taxes. It may also include the difference between the price at which the trade is executed and the price at which the order was intended to trade. Moreover, there is no payable stamp duty on futures transactions in the UK, while the index future requires a single transaction for buying or selling.

Fleming, Ostdiek, and Whaley (1996) estimate the effective bid-ask spread on S&P 500 futures to be about $30 per contract. In the cash indexes, trading costs are orders of magnitude higher than in the futures. These authors estimate that trading S&P 500 futures costs about 3% of the cost of trading an equivalent portfolio of index stocks. Sutcliffe (1997) indicated that the size of transactions costs for FTSE100 index futures are 10% of the cost of trading shares in the FT-SE100 and estimated at 0.116% compared to that of shares being 1.7%. He also showed that the round trip cost of trading 10 Nikkei Stock Average futures contracts is 0.178% which is 5% of the cost of trading the shares (3.604%). According to Blake (2000), the trading cost in the stock index futures in the UK is estimated at 0.14% which is much cheaper than trading in the underlying shares of index (1.9%), thus the cost of a round trip with futures is nearly 14 times lower than the cost involving the underlying shares.

Due to the greater exposure to risk for shares, Yadav and Pope (1992b) show that the bid-ask spread for shares is larger than for index futures. They mentioned that the existence of transaction costs allow futures prices to fluctuate within a band around the fair price. Again, these costs include round-trip cash and futures market trading costs, transaction taxes, and the costs of borrowing fixed interest capital and index stocks. Yadav and Pope (1992b) mentioned that the round-trip transaction taxes are 0.5%, while the spread between synchronous ask and bid futures prices varied from about 0.1% to about 0.2% of index value and round-trip futures commissions are typically less than 0.05%. They also noted that cash market-related marginal transaction costs can be close to zero for market makers and for institutional arbitrageurs.

7.3 Methodology for Hedging with Futures.

This chapter investigates the practical effectiveness of several commodity and futures contracts for hedging the underlying market risk. The effect on portfolio risk and return will depend on the hedge proportion and on the composition of the portfolio being hedged. The market risk of the price fluctuation is thought to decline as futures delivery approaches, therefore the risk of the hedge may be minimised by using the contract with the closest delivery date to the planned horizon date. As a traditional hedge may not minimise risk perfectly because the cash and the futures markets may not move perfectly together, the minimum variance hedge ratio takes account of this lack of perfect correlation and identifies the hedge ratio which minimises risk. The hedging strategy involves adopting a futures position that is equal in magnitude but opposite in sign to the established cash position. However, estimating the optimal hedge ratio may use the time-varying conditional variance models as noted in chapter 4. Hedging is often better than not hedging at all as suggested in chapters 5 and 6.

The methodology in this chapter relies heavily on the discussion of hedging practicalities presented in Blake (2000, pp 604-611). To illustrate the method, suppose that a fund manager wishes to use futures to hedge a portfolio over a particular period of time in order to avoid market risk, with the portfolio, hedge ratio, tick value, cash value and futures contract values all known. The fund manager is concerned with price fluctuations which increase the risk of holding the portfolio. A futures hedge is an act that reduces the price risk of an existing or anticipated position in the cash market. The fund manager hedges against the overall risk taking into consideration that if the cash market falls then this is offset by gains on the futures. Meanwhile, if the cash market rises this is offset by losses on the futures. In order to hedge a long position, the fund manager needs to sell a number of futures contracts and also the fund manager needs to calculate the cost of hedging.

Suppose the date is 1st January 1999 and a fund manager is uncertain about where the UK stock market is going over the next year. He may decide to hedge using futures in order to offset the risk created by the uncertainty in the market. The out-of-sample time period applied in this chapter requires that each delivery month contract is rolled over. In the construction of continuous futures returns series, the rollover dates are shown as the last trading day of the month prior to expiry, i.e. 26/02/99, 31/05/99, 31/08/99 and 30/11/99. The start of the trading period for each contract is the first trading day of the preceding contract's expiry month.

Consider that the fund manager wishes to hedge a £1 million UK stock portfolio which has a minimum variance hedge ratio (beta) of 0.8372. On 1st January 1999, the FTSE100 index stood at 5882.6 and the value of the March FTSE100 futures contract on LIFFE was 5868. The value of each index point movement (tick) in the LIFFE FTSE100 contract is £10.[1] The fund manager needs to calculate the number of futures contracts that have to be sold in order to hedge the portfolio.

Number of contracts = (Value of cash exposure/(Tick value*Futures price)) * β (7.1)

where β is the hedge ratio. Using the data in my example, the fund manager should sell 14.27 futures contracts. The portfolio value that the fund manager is locking in is based on the index value of the March contract, as long as the futures contracts are held to expiry. The hedged portfolio will have a value on the expiry date (say 21st March), whatever happened to the cash market index between 1st January and 21st March, which is determined by the following formula:

Terminal value of hedged fund = Initial value of hedged fund $* [1 + (((p^f_{(1\,Jan)} - p^s_{(1\,Jan)})/p^s_{(1\,Jan)}) * \beta)]$ (7.2)

Where, p^f is the futures price and p^s is the value of the cash index. Therefore, in my example, the

[1]Table 7.1 presents tick value for all contracts used in the empirical analysis in this chapter.

fund manager locks in the current value of the futures index for the expiry date of the contract. In this case, the value is £ 997,922.2 as shown in Figure 7.1, the portfolio value is fixed as the cash and futures positions are correlated. The fund manager locks in the current value as in Figure 7.1. The reason that the portfolio value is fixed for 21st March 1999 is that the cash and futures market positions are exactly offsetting. If the index rises between 1st January 1999 and 21st March 1999, the value of the cash portfolio rises by a certain amount and offsets the fall in the value of the futures contract. Alternatively, if the index falls over the same period, the cash portfolio falls by an amount which offsets the rise in the value of the futures contract. Figure 7.1 shows the terminal value of a hedged fund.

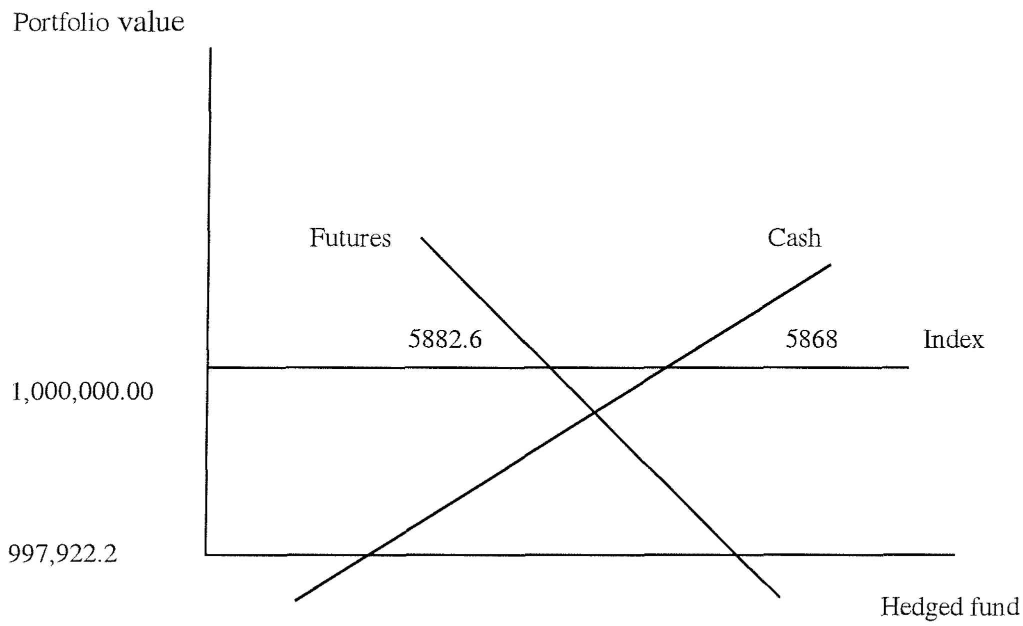


Figure 7.1 - The Terminal Value of a Hedge Fund

The terminal value of the cash fund can be calculated as follows:

Terminal value of cash fund = Initial value of cash fund $* [\ 1 + ((p^s_{(21\ March)} - p^s_{(1\ Jan)})/p^s_{(1\ Jan)})*\ \beta]$

$$\textbf{Terminal value of cash fund} \approx \text{Initial value of cash fund} * [\, 1 + ((p^{f}_{(1\ Jan)} - p^{s}_{(1\ Jan)})/p^{s}_{(1\ Jan)})*\beta + ((p^{s}_{(21\ March)} - p^{f}_{(1\ Jan)})/p^{f}_{(1\ Jan)})*\beta] \quad (7.3)$$

Where, $p^{s}_{(1\ Jan)}$ is the current value of the price index, $p^{f}_{(1\ Jan)}$ is the current value of the futures price, while $p^{f}_{(21\ March)}$ and $p^{s}_{(21\ March)}$ are the futures price and index price on the expiry date of the March contract. As stated by Blake (2000), the above equation decomposes the total change in the value of the cash portfolio into the difference between the initial cash index and the initial futures index, and the difference between the initial futures index and the final cash index. The decomposition is approximate and uses the result that:

$$((C-A)/A) \approx \ln C - \ln A$$
$$((C-A)/A) = \ln C - \ln B + (\ln B - \ln A)$$
$$((C-A)/A) \approx ((C - B)/B) + ((B - A)/A)$$

It is accurate if A, B, and C are all fairly close together.

If the futures position is a short position, then it will produce a loss equal to:

$$\textbf{Loss on futures position} = -\text{Number of contracts} * \text{Tick Value} * (p^{s}_{(21\ March)} - p^{f}_{(1\ Jan)}) \quad (7.4)$$

$$= -\text{Initial value of cash fund} * ((p^{s}_{(21\ March)} - p^{f}_{(1\ Jan)})/p^{f}_{(1\ Jan)})*\beta$$

The terminal value of the hedged portfolio at the end of the period is therefore given by adding (7.3) and (7.4), which is equal to the terminal value of hedged portfolio (7.2).

Terminal value of hedged fund (7.2) = Terminal value of cash fund (7.3) + loss on futures position (7.4)

The hedge may be viewed as perfect since the terminal value of the fund was known with certainty on 1st January irrespective of what eventually happened to the cash index. However, the fund manager may be better off without hedging, which occurs where the cash index rises above the end of period futures value. Meanwhile, the fund manager would make a healthy profit if the index fell compared to the end of period futures price.

The hedge efficiency for the period of the hedge is calculated as follows:

Hedge Efficiency = Gain (loss) on futures position / Gain (loss) on cash exposure (7.5)

The aim is to achieve hedge efficiency of 100%, whereby risk is eliminated. However, the actual outcome is likely to be higher or lower. The fund manager may find it difficult to perfectly hedge his portfolio, because without the approximation used above, the terminal value of the hedged portfolio is not independent of the terminal value of the cash portfolio. A second reason may arise from the indivisibility of the futures contract. In my example, the perfect hedge was based on 14.27 contracts and fractional contracts do not exist. Further, the fund manager may also find it difficult in practice to hedge his portfolio exactly because of the interest on the initial and variation margin payments.

For the purpose of this chapter, the main interest is in the further difficulty of perfect hedging due to the duration of the hedge. If the fund manager wishes to hedge from say 1st January 1999 until 26th February 1999, then there is some risk that the futures price will not be perfectly correlated to the cash price. If the fund manager is long cash and short futures, the concern may be that the cash price will fall and the futures price will rise. This means that losses will occur on both sides of the hedge. This is known as basis risk, where basis is defined as:

Basis = futures price (p^f) - cash price (p^s) (7.6)

Basis risk arises because of changes in dividend yields, interest rates, or other announcements. If the convergence of the cash and futures prices is smooth and linear, then the fund manager can estimate the basis on 26th February 1999, using the cash and futures prices on 1st January 1999.

Estimated Basis (26 February) = (No of days 26 Feb to 21 Mar / No of days 1 Jan to 21 Mar)*$[p^f_{(1\ Jan)} - p^s_{(1\ Jan)}]$ (7.7)

In my example, the estimated basis is -3.8325. The fund manager might expect to lock in an index value of (Price Index + Estimated Basis at 26 Feb) by selling the 14.27 contracts, as seen in Figure 7.2.

Value of hedged portfolio (26 Feb) = Initial value of cash fund * $[1 + ((p^f_{(1\ Jan)} - p^s_{(1\ Jan)})/p^s_{(1\ Jan)})*\beta) + (p^s_{(26\ Feb)} - p^f_{(1\ Jan)})/p^f_{(1\ Jan)})*\beta) - ((p^s_{(26\ Feb)} + Basis_{(26\ Feb)} - p^f_{(1\ Jan)}/p^f_{(1\ Jan)})*\beta)]$

Value of hedged portfolio (26 Feb) = Initial value of cash fund * $[1 + ((p^f_{(1\ Jan)} - p^s_{(1\ Jan)})/p^s_{(1\ Jan)})*\beta) - ((Basis_{(26\ Feb)}/p^f_{(1\ Jan)})*\beta)]$ (7.8)

From the example, the basis is -3.8325, but if the basis increases (in absolute terms) the fund manager will suffer losses on the hedged portfolio, and will experience gains when the basis declines (in absolute terms). This happens because the fund manager is long in cash and short in futures. The value for the hedged portfolio on 26th February 1999 will be less when the (absolute) basis increases but still better than not hedging at all. However, a long hedger is short cash and long futures and consequently long the basis. This means that the hedger gains when the (absolute) basis increases and loses when the (absolute) basis narrows. Figure 7.2 demonstrates estimating the basis by linear interpolation.

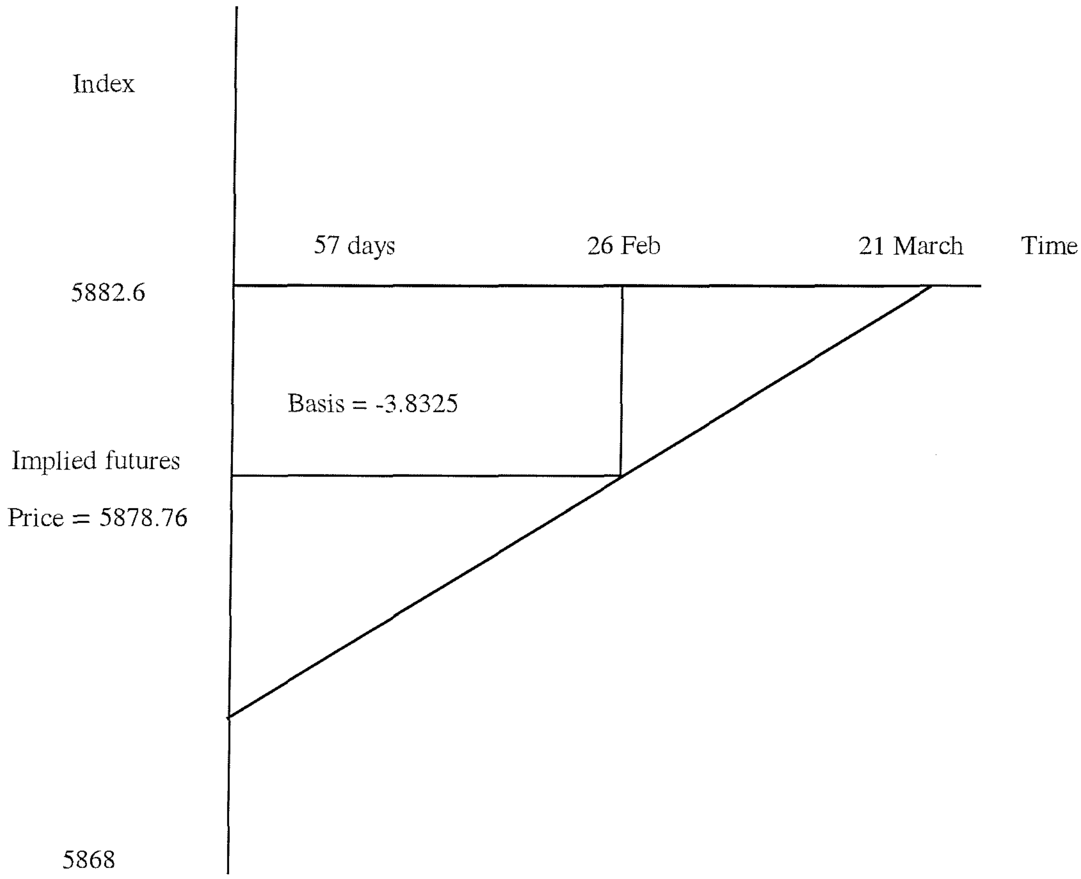


Figure 7.2 - Estimating The Basis by Linear Interpolation

As stated earlier, the basis represents the difference between the futures price and the price of the underlying asset. There will be a different basis for each delivery month, where before the delivery date the future price could be above or below the cash price. These situations are known as contango and backwardation.[2] From Figure 7.2, the case of backwardation occurred. However, the basis tends to zero as the contract approaches delivery.

According to Blake (2000) hedging using futures contracts does not eliminate risk entirely, unless the contracts are held to expiry. Meanwhile, if the futures position is closed before expiry, the fund manger has swapped market risk for basis risk. For the constant hedge ratio method in the above example for the FTSE 100, the number of contracts are calculated by (7.1). The portfolio value that fund manager is locking in is based on the value of the index value of futures contract

[2]See chapter 2, section 2.1 and 2.5.

as long as the futures contract are held to expiry, whatever happened to the cash market index during the contract life, the hedge portfolio is determined by the equation (7.2). The value of the cash fund is calculated by equation (7.3). To calculate the hedge efficiency for the constant minimum variance hedge method, the loss/gain on futures position is estimated by applying the equation (7.5) where the value of the FTSE100 index is known and the value of the March contract on LIFFE is also known. The value of each one point movement (tick value) in the LIFFE FTSE100 contract is worth £10. The loss/gain on cash exposure is calculated by subtracting the terminal value of the cash fund from the initial value of cash fund.

For the application of the time-varying hedge method in this chapter, the number of contracts needed for the fund manager to sell in order to hedge the portfolio exactly are again calculated by applying the equation (7.1) with daily time-varying hedge ratios and then determining the difference between the number of contracts from one day to the next. As the fund manager may hedge daily, there is some risk that the futures price will not move in line with the cash price. The risk of this happening is known as basis risk. The estimated basis at the end of the hedge is calculated for every contract on a daily basis using equation (7.7). The portfolio value that the fund manager is locking in is estimated based on equation (7.2) and the terminal value of cash portfolio is estimated by equation (7.3) on a daily basis. The terminal value of the cash portfolio rises or falls by an amount that exactly offsets the fall or rise in the value of the futures contract, respectively. Subsequently, for the time-varying hedge method, the summation of the daily loss/gain of futures position and the summation of the cash exposures for each contract are estimated, and the hedge efficiency then measured for each contract for the one and two year time periods applying the equation (7.5).

7.4 Summary Statistics.

This section presents summary data for the minimum variance and time-varying hedge ratios applied in this chapter. Tables 7.2 and 7.3 present summary statistics on hedge ratios for the stock markets for the one year and two year out-of-sample time periods, respectively. The variance was noted to be small in Australia, Germany, UK and the US for both GARCH and GARCH-X, while it was noted to be relatively large in Hong Kong for GARCH!and GARCH-X. From Table 7.2, the maximum value of the GARCH hedge ratio is 1.0571 in the UK series and the minimum value is -0.0219 in Hong Kong. The range varies considerably across cases and is seen to be at its widest at 0.9273 and 0.6721 in Hong Kong for both GARCH and GARCH-X models. This may be caused by the Asian financial market crisis in late 1990's. The smallest ranges are for Australia in Table 7.2 and for Australia and Japan in Table 7.3.

Table 7.3 presents the summary statistics for the two year out-of-sample time period for the stock index markets. The constant minimum variance hedge ratios are noted to be all positive and less than one. The time-varying hedge ratio has its maximum value of 1.1237 and the minimum value of -0.0087 in Hong Kong in the GARCH-X method. The highest range is estimated at 1.1547 and 1.1324 in Hong Kong for the GARCH and GARCH-X, respectively.

Table 7.4 presents summary statistics for the commodity markets. Here, there is only the O3 case for the one year out-of-sample time period where the time-varying hedge methods out-performed the constant minimum variance method (see chapter 6). The variance and range are smaller in the GARCH case than for the GARCH-X. Table 7.4 also presents the cases of O3 and Cocoa for the two year out-of-sample time period. The range and variance are noted to be higher for O3 for both GARCH and GARCH-X. The maximum time-varying hedge ratio is less than one in the Cocoa series and more than one in the O3 series.

7.5 Results on Time-Varying Hedging with Transactions Costs.

The analysis in this section aims to identify the practical effectiveness of hedging according to the findings of chapters 5 and 6, among the cases where the time-varying hedge performs better than the constant minimum variance hedge. The hedge efficiency is calculated for both the constant minimum-variance and time-varying methods. The various approaches to the calculations for the time-varying hedge methods are denoted as GARCH 'Base' and GARCH-X 'Base' models, GARCH 'Threshold' and GARCH-X 'Threshold' models and then 'Transaction Costs' are introduced to the GARCH and GARCH-X models to identify the effect on the hedge efficiency.

For the 'Base' model the hedge efficiency is estimated for each contract's period as the front month contract, where the portfolio is re-balanced on a daily basis. The summation of loss/gain on futures position and summation of loss/gain on cash exposure are calculated across the days of each contract. The hedge efficiency is estimated for each contract for one and two year out-of-sample time periods. For the 'Threshold' model, the portfolio is not re-balanced daily but rather is re-balanced only when the difference of contracts to be held as implied by the change in hedge ratio is at least one futures contract. Then, the 'Transaction costs' model is applied to the 'Threshold' case. Here, the cumulative trading is calculated for the portfolio over each contract period and transactions costs are applied prior to calculating hedge efficiency. Two sizes of transactions costs values for FTSE100 (0.116%) and Nikkei Stock Average futures contracts (0.178%) are considered to be the lowest and highest, respectively (see Sutcliffe, 1997).

If the convergence of the cash and futures prices is assumed to be smooth and linear, the basis can be estimated daily by applying the equation (7.7) for each contract. For March contract in the out-of sample period, the cash price is 1st January and the expiry date is the 21st March and the June contract the cash price is 1st March and the expiry date is 21st June, while for the September contract the cash price is 1st June and the expiry date is 21st September. The cash price for the December contract is 1st September and the expiry date is 21st December and the cash price for the March contract is taken on 1st December and the expiry date is on 21st March. The hedge efficiency is measured for each contract applying the model explained above.

The evidence is presented in Tables 7.5 to 7.18. A perfect hedge is achieved when the hedge efficiency is 100%. This is expected for the GARCH and GARCH-X 'base' models prior to setting a threshold or introducing transaction costs. The comparisons of particular interest are between the 'Base' model versus minimum variance, 'Threshold' model versus 'Base' model, 'Transaction costs' model versus 'Threshold' model and 'Transaction costs' model versus minimum variance hedge ratio model.

7.5.1 'Base' Model.

The first step is to analyse the hedge efficiency of time-varying methods against the minimum variance method. The calculations applying GARCH and GARCH-X hedge ratios are done for the one and two year out-of-sample cases selected as appropriate from chapters 5 and 6. The hedge efficiency is calculated by applying equation (7.5) (see section 7.3 for full details).

In the stock markets, considering the hedge efficiency for Australia shown in Table 7.5, the GARCH 'base' and GARCH-X 'base' methods out-perform the constant minimum variance method in 4 out of 5 contract periods in the one year out-of-sample time period. The GARCH 'base' model for Australia two year period consistently out-performs the minimum variance method in each contract period (see Table 7.6). Germany hedge efficiency for one and two year out-of-sample time periods presented in Tables 7.7 and 7.8, respectively, are seen to be close to 100% in the GARCH 'base' and GARCH-X 'base' models . The GARCH 'base' and GARCH-X 'base' models under-perform compared to the minimum variance method in 3 out of 5 contract periods in the one year out-of-sample time period and again under-perform in 6 out of 9 contract time periods in the two year period in Hong Kong (see Tables 7.9 and 7.10).

Hedge efficiency for Japan was measured for the two year out-of-sample time period only according to the percentage changes in variance indicated in chapter 5 (Tables 5.35 and 5.36). From Table 7.11, GARCH 'base' and GARCH-X 'base' generally under-perform compared to the constant minimum variance method in most cases. From Table 7.12 and 7.13, the GARCH 'base' and GARCH-X 'base' in South Africa out-perform the minimum variance method in every case for one and two year out-of-sample time periods. Table 7.14 shows that the GARCH 'base' and GARCH-X 'base' perform better in 4 out of 5 cases in comparison to the constant minimum variance method in the UK market. Meanwhile, the US hedge efficiency is much closer to 100% than the constant method as indicated in Table 7.15.

The hedge efficiency in commodity markets is calculated for Gas Oil (O3) for one and two year out-of-sample time periods and for Cocoa market for the two year out-of-sample time period only. Tables 7.16 and 7.17 indicate that the constant minimum variance method out-performs the

GARCH 'base' and GARCH-X 'base' in 3 out of 5 and in 7 out of 9 contracts period in the one year and two year time periods, respectively. In Table 7.18, GARCH 'base' and GARCH-X 'base' consistently out-perform the constant method in every contract time period.

In general, as expected, the GARCH and GARCH-X 'base' methods produce hedge efficiency figures close to 100%. However, as in chapter 5 and 6 there is considerable variation in performance across the markets studied.

7.5.2 'Threshold' Model

I have used 'Threshold' to denote the cases where the portfolio is not re-balanced daily but rather is only re-balanced when the day-to-day difference of contracts implied by the daily change in hedge ratio is at least one futures contract. The hedge efficiency is calculated applying equation (7.5), with full explanation in section 7.3.

In general, as expected, the less frequent re-balancing comes at a cost which is seen in reduced hedge efficiency (further away from 100%). In this section, the focus of comparison is between the 'Threshold' model and the 'Base' model. Table 7.5 presents Australia results, where the GARCH 'Threshold' under-performs compared to GARCH 'Base' in all cases and under-performs in 4 out of 5 cases for the GARCH-X method for the one year period. Again, the hedge efficiency in Australia is better using the GARCH 'Base' method in every case for the two year time period as seen in Table 7.6. Meanwhile, Table 7.7 and 7.8 indicate that the hedge efficiency for Germany in both out-of-sample time period is better applying the 'Base' model for both GARCH and GARCH-X. From Tables 7.9 and 7.10 for Hong Kong, GARCH 'Base' and GARCH-X 'Base' perform better than the GARCH 'Threshold' and GARCH-X 'Threshold' in 3 out of 5 and in 7 out of 9 contract periods for one and two year out-of-sample time periods, respectively.

For the Japan series (Table 7.11), there are no cases where the implied daily change in contracts held is greater than or equal to 1. Therefore, the 'Threshold' method as defined implies no portfolio re-balancing. In this particular case, the hedge efficiency is measured from the start of every contract during the two year out-of-sample time period. By referring to Tables 5.35 and 5.36 in chapter 5, note that the percentage change in variance for the Japan case is very close to zero. This finding further justifies the selections of the cases involved in this chapter, to be only those where time-varying methods out-perform the constant minimum variance method in chapters 5 and 6.

From Tables 7.12 and 7.13, the 'Base' model out-performs the 'Threshold' model in both one and two year periods for the South Africa case. The same occurs in the UK and the US cases in Tables 7.14 and 7.15, respectively.

For the commodity markets in Table 7.16 to 7.18, the 'Base' model generally out-performs the 'Threshold' model as expected. There are exceptions (1 in Table 7.16, 7 in Table 7.17 and 3 in Table 7.18).

Hedge efficiency can be observed for some contract periods as having extreme values of a very low/high percentage. These values occur due to cases where the basis risk arises, where some shocks happened because of changes in the markets. Here, futures and cash prices do not converge smoothly toward the expiry date, which indicates some jump in either cash or futures prices. Overall, as expected, the hedge efficiency for GARCH 'Threshold' and GARCH-X 'Threshold' models are generally inferior to the 'Base' models. This is consistent with the prior expectation that, although re-balancing less frequently will reduce transaction costs, hedge efficiency is also reduced.

7.5.3 'Transaction Costs' Model.

This section augments the 'Threshold' case by introducing transaction costs. The estimated transaction costs in this investigation were obtained from Sutcliffe (1997) (see section 7.2). Two possible values of transaction costs are used. According to Sutcliffe (1997), the size of transaction costs for FTSE100 stock index futures is estimated at 0.116%. This figure was taken as a 'low' level of transaction cost, while a 'high' value of transaction cost was taken to be 0.178% as this was shown to be the cost of trading in Nikkei Stock Average futures contracts. These two values are applied as the 'low' and 'high' transaction costs for all series involved. Tick values from Table 7.1 are used for each market along with the futures prices for each contract to calculate the trading cost per contract. The cumulative trading quantities are calculated from the difference in the number of contracts implied by the hedge ratios from one day to the next, where daily re-balancing only occurs if the change is at least one contract.

In the case where the transaction costs introduced are estimated at 0.116%, from Table 7.5, the Australia hedge efficiency is better for the GARCH 'Threshold' compared to GARCH 'Transaction costs' in every case for the one year out-of-sample time period, whereas the GARCH-X 'Transaction cost' model performs better than GARCH-X 'Threshold' in 2 out of 5 contracts in the same time period. By introducing the low (0.116%) or the high (0.178) transactions costs to the GARCH 'Threshold' model, Table 7.6 indicates that the GARCH 'Transaction costs' model performs better than GARCH 'Threshold' in 4 out of 9 contract periods in the two year time period. In Table 7.7, Germany hedge efficiency applying GARCH and GARCH-X is better in 4 out of 5 and 3 out of 5 contracts respectively, when introducing transaction cost. In Table 7.8, Germany hedge efficiency for the two year period compared better in 5 out of 9 cases using GARCH 'Transaction cost' and under-performs in 5 out of 9 cases compared to GARCH-X 'Threshold'.

Hong Kong results are presented in Table 7.9, where the GARCH 'Transaction costs' is seen to perform better in 2 out of 5 contracts only compared to the GARCH 'Threshold' in both transaction costs values cases. The GARCH-X 'Transaction costs' performs better in one contract period. However, in Table 7.10 for the two year time period, GARCH 'Transaction costs' under-performs in comparison to the GARCH 'Threshold' in all contracts but one for the low and high transactions costs. The GARCH-X 'Transaction cost' under-performs compared to the GARCH 'Threshold' in 6 out of 9 contract periods. Table 7.11 presents the Japan results, where the transactions costs of 0.116% and 0.178% are introduced to the GARCH 'Threshold' model at the start of each contract period since there is no daily re-balancing of the portfolio because daily implied changes in futures contracts are always less than one (see section 7.5.2). In this case, GARCH 'Transaction costs' performs better that GARCH 'Threshold' when accounting for the

low and high costs. The same is true for the GARCH-X 'Transaction costs' model. However, both GARCH 'Transaction cost' and GARCH-X 'Transaction cost' under-perform compared to the minimum variance model.
Tables 7.12 and 7.13 present the South Africa one and two year out of sample periods, respectively. From Table 7.12, the GARCH 'Transaction costs' performs better in 2 out of 5 contracts compared to the 'Threshold' model for the low and high transaction costs. The same occurs for the GARCH-X 'Transaction costs' when compared to the GARCH-X 'Threshold'. However, from Table 7.13 the GARCH 'Transaction costs' model out-performs the GARCH 'Threshold' model in 2 out of 9 contract periods for low and high transaction costs. The GARCH-X 'Transaction costs' out-performs the GARCH-X 'Threshold' in 2 out of 9 contract periods in the low transaction cost case, while the GARCH-X 'Transaction costs' under-performs in all contract periods when the higher transaction cost is assumed. For the case of the UK series in Table 7.14 the hedge efficiency using GARCH 'Transaction costs' model is better in 3 out of 5 contract periods and only better in one contract period applying the GARCH-X 'Transaction costs' model. Meanwhile, Table 7.15 indicates that the hedge efficiency in the US series is better applying the 'Threshold' model for the GARCH and GARCH-X.

In the commodity markets, Table 7.16 presents the O3 results, where the GARCH 'Transaction costs' model under-performs in 3 out of 5 contract periods in comparison to the GARCH 'Threshold' model, while GARCH-X 'Transaction cost' performs better in 3 out of 5 contract periods in comparison to the GARCH-X 'Threshold' model. Meanwhile, for the same series for the two year out-of-sample time period, the GARCH 'Transaction costs' under-performs in most contract periods compared to the GARCH 'Threshold' model. The GARCH-X 'Transaction costs' performs better in 5 out of 9 contract periods in comparison to the the GARCH-X 'Threshold' model. Table 7.18 presents the Cocoa series, where the GARCH 'Transaction cost' does better in 3 contract periods in the low transaction costs case and 4 out of 9 contract periods for the high transaction cost in comparison to the 'Threshold' model. Meanwhile, the GARCH-X 'Transaction costs' does better in 7 out of 9 contract periods in the low transaction cost and 8 out of 9 in the high transaction cost case.

I now turn to consider the comparison with the constant minimum variance method. The higher value of transaction costs assumed is 0.178% across all cases under investigation. Tables 7.5 and

7.6 present Australia hedge efficiency for one and two year out-of-sample time periods. GARCH and GARCH-X underperform when compared to the minimum variance method in 4 out of 5 and in 3 out of 5 cases, respectively when the maximum transaction costs are introduced, while, GARCH 'Transaction costs' performs better than the minimum variance in 4 out of 9 in the two year out-of-sample period. In Tables 7.7 and 7.8 for Germany the GARCH and GARCH-X consistently under perform in comparison to the minimum variance after the introduction of the higher value of transaction costs. Tables 7.9 and 7.10 for Hong Kong indicate that the GARCH 'transaction cost' under-performs in 4 out of 5 cases when the lower transaction cost is considered and consistently under-performs in all contracts for the higher value transaction cost. The GARCH-X 'transaction cost' under-performs in 4 out of 5 contract period when compared to the minimum variance model in the one year period. In the two year out-of-sample period, the GARCH 'Transaction cost' and GARCH-X 'Transaction cost' models under-perform compared to the minimum variance model. The GARCH 'Transaction costs' and GARCH-X 'Transaction costs' models perform well in 2 out of 9 in the low transaction costs case and also perform better in 2 out of 9 in the high transaction costs cases.

The Japan results indicate that the hedge efficiency is much better for the minimum variance model than for the GARCH 'Transaction cost' and GARCH-X 'Transaction cost' when both lower and higher values of the transactions cost are taken into account. This is again expected after the transaction costs are considered, as the time-varying methods for the two year out-of-sample period only slightly out-perform the constant variance method as shown in Chapter 5. The hedge efficiency in the South Africa case is consistently estimated to be around 100% in the one and two year time periods applying the GARCH 'Transaction costs' and GARCH-X 'Transaction cost' as indicated in Tables 7.12 and 7.13. Meanwhile Tables 7.14 and 7.15 indicate that introducing the transaction cost reduce the hedge efficiency in the UK and the US markets in 4 out of 5 contracts periods.

In the commodity markets, the Gas Oil (03) hedge efficiency for the minimum variance method for one and two year periods is closer to 100% in all contract periods but one. This indicates that the introduction of transaction costs reduces hedge efficiency. However, in the Cocoa series the hedge efficiency is close to 100% for the low and high transaction costs applied in comparison to the minimum variance model for both GARCH 'Transaction cost' and GARCH-X 'Transaction cost' model.

The general findings are that when the transaction costs are introduced the hedge efficiency decreases in most of the cases as expected. In the case when the 'Transaction costs' model is compared to the 'Threshold' model, the results indicate reduced hedge efficiency. However, the hedge efficiency reduced significantly when considering the 'Transaction costs' model in comparison to the minimum variance model in most of the cases under investigation. The reduction in hedge efficiency varies in most cases in both one and two year out-of-sample period for the stock and commodity markets. This reflects the variation in percentage change of variance figures indicated in chapters 5 and 6. As the Japan case showed, a marginal reduction in variance when comparing time-varying hedge ratio methods to the constant variance hedge method is insufficient to offset the transaction costs. The results clearly illustrate that the smaller the percentage reduction in variance achieved by time-varying hedging, the less likely that this will be sufficient to cover transaction costs.

7.6 Conclusion.

The investigation of the hedge effectiveness for the out-of-sample time period is conducted between the minimum variance, GARCH and GARCH-X method. The calculations for the time-varying hedge methods are denoted as 'Base', 'Threshold' and 'Transaction costs' as explained in section 7.5. This chapter contributes to the existing literature since there has been a lack of research evidence on the trade off between risk reduction and transaction costs. An alternative strategy which involves less frequent re-balancing, such as re-balancing only when the optimal hedge ratio changes by some fixed amount was carried out. This investigation between the trade off between the risk reduction and transaction cost in this chapter illustrated the practicality of the hedging methods.

The hedging efficiency for the selected cases of the out-of-sample time period varies from one case to another when applying the models involved. This occurs as a results of the adverse movements in security prices which increase the overall risk on the position taken. The hedging efficiency was estimated and as expected the GARCH 'Base' and GARCH-X 'Base' indicated consistent higher hedge efficiency in comparison to the minimum variance hedge ratio. As expected the hedge efficiency for GARCH 'Base' and GARCH-X 'Base' have percentages equal to around 100%. Hedge efficiency can be observed for some contract periods as having extreme values. These values occur due to occasions where the basis risk arises, where some shocks happened because of changes in the markets. As a result, the futures and cash prices do not converge smoothly toward the expiry date, due to jumps in either futures or cash prices.

The percentage change in variance for the out-of-sample time periods for the stock and commodity futures markets in Tables 5.28, 5.29, 5.35, 5.36, 6.23, 6.24, 6.30 and 6.31 are investigated. The 'Base' model produces hedge efficiency figures close to 100% as expected for many cases. However, introducing the minimum and maximum transaction costs to the 'Threshold' model indicates reduced hedge efficiency when compared to the 'Base' and the constant minimum variance hedge method. The cases investigated indicate that the percentage changes in variance are different from one case to another. The cases where the percentages of variance are small seem to under-perform after introducing the transaction costs. This indicates that introducing transaction costs in the time-varying method reduce hedge efficiency even further in comparison to the constant minimum variance hedge method. The overall conclusion is that time-varying hedging is often inferior to the constant minimum variance hedge when transaction costs are taken into consideration. This is more evident in the commodity markets than the stock markets.

Table 7.1

Futures Markets Tick Value

Futures Markets	Tick Value	Sources
SFE All Ordinaries SPI	$10	www.asx.com.au
EUREX DAX	Euro 10	www.eurexchange.com
HKFE Hang Seng	$5	www.hkex.com.hk
Nikkei 225 Stock Average	$25	www.cme.com
SAFEX Industrial 25	R10	www.safex.co.za
FTSE 100	£10	www.liffe.com
S&P500	$12.50	www.cme.com
Gas Oil	$25	www.sucden.co.uk
Cocoa	$10	www.liffe.com

Table 7.2

Summary Statistics for Stock Index Markets (One Year Out-of-Sample Period)

One year out-of-sample	Observations	Minimum Var Hedge Ratio (β)	Time-Varying Methods					
			Mean	Std Error	Variance	Min	Max	Range
Australia GARCH	261	0.6805	0.71878	0.03366	0.00113	0.5639	0.8152	0.2513
Australia GARCH-X	261	0.6805	0.71801	0.03155	0.00099	0.6223	0.8199	0.1976
Germany GARCH	261	0.7504	0.85709	0.04699	0.00221	0.6692	0.9744	0.3052
Germany GARCH-X	261	0.7504	0.85423	0.04494	0.00202	0.6833	0.9898	0.3067
Hong Kong GARCH	261	0.8159	0.7073	0.15245	0.02324	-0.0219	0.9053	0.9273
Hong Kong GARCH-X	261	0.8159	0.72722	0.11548	0.01334	0.2378	0.9098	0.6721
South Africa GARCH	261	0.6197	0.63636	0.07446	0.00555	0.2678	0.8477	0.5799
South Africa GARCH-X	261	0.6197	0.63651	0.07665	0.00588	0.2914	0.8505	0.5592
UK GARCH	261	0.8372	0.9861	0.03521	0.00124	0.7827	1.0571	0.2744
UK GARCH-X	261	0.8372	0.8589	0.03272	0.00107	0.6736	0.9487	0.2751
US GARCH	261	0.8919	0.90677	0.05195	0.00269	0.6979	1.0479	0.3500
US GARCH-X	261	0.8919	0.90663	0.05255	0.00276	0.6958	1.0493	0.3535

Table 7.3

Summary Statistics for Stock Index Markets (Two Year Out-of-Sample Period)

Two year out-of-sample	Observations	Minimum Var Hedge Ratio (β)	Time-Varying Methods					
			Mean	Std Error	Variance	Min	Max	Range
Australia GARCH	522	0.6717	0.72153	0.04655	0.00217	0.5031	0.8552	0.3521
Germany GARCH	522	0.7161	0.83975	0.07785	0.00606	0.4924	1.0586	0.5661
Germany GARCH-X	522	0.7161	0.83604	0.07696	0.00562	0.4781	1.0456	0.5676
Hong Kong GARCH	522	0.8029	0.75328	0.13022	0.01696	-0.0406	1.1141	1.1547
Hong Kong GARCH-X	522	0.8029	0.76439	0.11501	0.01323	-0.0087	1.1237	1.1324
Japan GARCH	522	0.9449	0.93281	0.05523	0.00305	0.7012	1.076	0.3748
Japan GARCH-X	522	0.9449	0.9335	0.05105	0.00261	0.7673	1.0791	0.3119
South Africa GARCH	522	0.5698	0.63703	0.08803	0.00775	0.2771	0.9240	0.6469
South Africa GARCH-X	522	0.5698	0.61338	0.09235	0.00857	0.2898	0.8878	0.598

Table 7.4

Summary Statistics for Commodity Markets

One year out-of-sample	Observations	Minimum Var Hedge Ratio (β)	Time-Varying Methods					
			Mean	Std Error	Variance	Min	Max	Range
O3 GARCH	261	0.7625	0.87619	0.10641	0.01132	0.4614	1.1046	0.6432
O3 GARCH-X	261	0.7625	0.84832	0.11988	0.01437	0.4223	1.1659	0.7437
Two year out-of-sample								
O3 GARCH	522	0.7556	0.84696	0.13396	0.01795	0.1231	1.1860	1.0629
O3 GARCH-X	522	0.7556	0.83304	0.15214	0.02315	0.0615	1.3654	1.3039
Cocoa GARCH	522	0.5744	0.64263	0.12088	0.01461	0.2032	0.9119	0.7087
Cocoa GARCH-X	522	0.5744	0.64134	0.125704	0.01580	0.2504	0.9096	0.6592

Table 7.5

Australia Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Cost'		GARCHX 'Base'	GARCHX 'Threshold'	GARCH-X 'Transaction Cost'	
				0.116	0.178			0.116	0.178
1/1-26/2/1999	100.301	102.797	17.601	3.084	1.894	102.795	104.471	108.790	111.249
1/3-31/5/1999	458.199	99.523	113.144	197.346	80.000	99.465	100.224	104.044	106.207
1/6- 31/8/1999	93.383	98.616	135.565	16.494	11.224	98.718	22.948	25.396	26.932
1/9- 30/11/1999	83.656	91.896	71.382	28.145	16.127	91.767	43.853	27.876	23.333
1/12-31/12/1999	107.555	99.896	305.371	3.426	2.224	99.890	67.898	84.135	96.465

Table 7.6

Australia Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'	
				0.116	0.178
1/1 - 27/02/1998	75.750	100.426	78.859	86.904	87.896
2/3 - 29/05/1998	37.441	99.352	98.769	87.926	89.499
1/6 - 31/08/1998	97.079	98.836	84.429	0.019	0.012
1/9 - 30/11/1998	93.668	101.407	103.699	105.942	107.181
1/12/98 -26/2/99	69.554	100.384	87.530	93.814	94.903
1/3 -31/5/1999	458.193	99.524	108.839	115.637	119.630
1/6 -31/8/1999	93.383	98.615	202.476	149.139	130.733
1/9 - 30/11/1999	83.656	91.043	71.520	74.041	75.462
1/12 - 31/12/1999	107.551	99.896	309.393	1457.327	1482.416

Table 7.7

Germany Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-26/2/1999	169.437	99.743	1.298	1.574	1.776	99.739	23.148	25.067	26.229
1/3-31/5/1999	96.599	100.192	58.016	59.948	61.034	100.197	54.491	56.284	57.292
1/6- 31/8/1999	97.287	101.530	11.229	13.231	14.625	101.531	65.721	164.521	799.099
1/9 - 30/11/1999	93.500	97.657	207.903	173.321	159.169	97.676	203.601	170.971	158.481
1/12-31/12/1999	93.822	100.999	288.368	330.388	358.293	100.999	180.393	221.258	252.737

Table 7.8

Germany Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-27/2/1998	93.699	99.096	1.532	4.337	4.398	99.089	23.393	45.429	43.285
2/3 - 29/5/1998	89.219	99.646	295.007	174.232	190.715	99.657	34.477	33.309	33.947
1/6 - 31/8/1998	98.902	100.032	92.241	89.431	90.176	100.027	257.334	5946.361	8247.981
1/9 - 30/11/1998	63.132	101.315	72.722	79.373	83.453	101.327	3.667	3.705	3.726
1/12/98 -26/2/99	78.941	99.234	105.939	129.111	135.287	99.233	3419.739	744.616	600.776
1/3-31/5/1999	96.659	100.198	61.345	62.911	63.782	100.201	227.363	210.609	202.629
1/6-31/8/1999	97.287	101.529	159.849	190.643	212.526	101.532	12.072	12.315	12.448
1/9- 30/11/1999	93.500	97.668	204.048	172.645	158.217	97.679	82.891	29.938	22.318
1/12- 31/12/1999	93.822	100.999	181.316	223.145	255.531	100.999	58.199	19.965	14.776

Table 7.9

Hong Kong Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-26/2/1999	137.952	102.316	130.324	136.078	139.367	102.295	97.749	99.906	101.099
1/3-31/5/1999	103.520	111.045	48.038	51.841	54.131	108.134	33.463	31.156	30.049
1/6- 31/8/1999	94.484	113.859	86.823	89.059	90.302	113.932	102.210	105.304	107.036
1/9- 30/11/99	92.521	109.712	30.409	28.611	27.735	110.091	2394.329	13014.15	2931.37
1/12-31/12/99	95.925	99.846	100.056	94.819	92.239	99.866	97.269	85.169	79.859

Table 7.10

Hong Kong Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1 -27/1/1998	100.363	102.444	131.705	138.377	139.836	102.346	131.330	137.164	138.526
2/3-29/5/1998	97.544	118.697	55.329	46.845	46.263	119.455	1.540	43.102	41.534
1/6- 31/8/1998	95.763	113.517	58.706	57.044	56.193	109.785	76.522	74.628	73.654
1/9 - 30/11/1998	109.974	96.872	93.4891	93.085	92.969	97.455	97.799	97.456	97.274
1/12/98-26/2/99	199.486	77.966	123.938	136.017	139.533	76.3648	782.245	86.556	90.107
1/3 -31/5/1999	103.521	111.100	46.536	54.792	60.533	112.005	40.745	44.316	46.494
1/6 -31/8/1999	94.484	114.024	111.266	113.868	115.170	114.263	110.011	111.934	112.990
1/9- 30/11/1999	92.521	109.811	27.511	25.868	25.068	110.174	7.391	7.081	6.926
1/12- 31/12/1999	95.926	99.85	100.062	107.996	112.775	99.870	51.704	50.945	50.548

Table 7.11

Japan Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-27/03/1998	101.190	93.772	81423.372	105.867	69.023	93.891	81423.373	105.870	69.023
2/03-29/05/1998	97.849	3192.655	32.912	77.649	75.855	418.687	32.851	77.657	75.862
1/06- 31/08/1998	97.447	124.534	128.653	118.433	113.610	123.075	128.648	118.43	113.662
1/09- 30/11/1998	96.032	93.691	28.380	20.959	18.389	93.660	28.456	21.001	18.421
1/12/98-26/02/99	98.844	103.778	164.289	139.175	128.668	103.545	164.028	138.99	128.502
1/03-31/05/1999	102.202	102.445	77.925	81.983	84.330	102.487	77.935	81.933	84.342
1/06-31/08/1999	93.017	86.249	99.471	76.126	76.126	86.250	99.382	76.074	67.601
1/09- 30/11/99	109.548	109.001	33.304	35.787	37.271	108.820	33.378	35.872	37.364
1/12- 31/12/99	87.639	99.483	133.686	73.929	59.674	99.482	133.682	74.932	56.675

Table 7.12

South Africa Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH-X 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-26/3/1999	151.089	103.019	112.087	111.474	111.150	102.914	112.387	111.776	111.452
1/3-31/5/1999	315.024	100.201	101.861	101.579	101.429	100.116	78.265	101.413	101.180
1/6- 31/8/1999	1848.771	99.644	96.591	96.199	95.990	99.846	99.911	95.713	95.497
1/9 - 30/11/1999	134.751	98.855	98.266	97.683	97.375	98.904	102.133	95.651	95.387
1/12-31/12/1999	111.086	105.373	51.156	49.590	48.792	105.792	62.294	39.794	39.093

Table 7.13

South Africa Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-27/2/1998	165.761	103.118	112.37	112.074	111.960	102.766	108.447	107.411	107.234
2/3-29/5/1998	172.228	100.632	104.37	104.940	104.818	100.672	103.995	104.573	104.460
1/6- 31/8/1998	64.899	99.724	101.305	101.197	101.098	99.874	99.245	99.055	98.955
1/9- 30/11/1998	154.992	98.825	96.583	96.329	96.194	98.899	93.117	92.847	92.704
1 Dec98 -26/2/99	133.231	99.495	94.508	86.488	86.036	99.513	91.118	85.339	84.918
1/3/ - 31/5/1999	315.024	100.2001	99.734	99.478	99.343	100.112	95.047	95.249	95.039
1/6-31/8/1999	1848.771	99.618	96.873	96.409	96.161	99.869	97.766	97.358	97.143
1/9- 30/11/1999	134.750	98.879	95.887	95.409	95.156	98.952	93.952	93.458	93.195
1/12- 31/12/1999	111.086	105.352	45.390	25.069	20.229	105.907	51.460	29.379	23.898

Table 7.14

UK Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1 - 26/2/99	104.978	89.386	13.450	14.760	15.571	88.789	859.793	3187.400	906.815
1/3 -31/5/99	72.877	102.055	136.904	148.338	155.269	102.035	74.152	77.627	79.622
1/6- 31/8/99	1972.183	98.368	107.636	102.349	99.732	98.368	79.040	74.356	72.073
1/9- 30/11/99	76.794	101.807	126.545	130.698	133.032	101.774	210.946	255.176	287.482
1/12-31/12/99	97.171	100.223	101.553	106.485	109.323	100.243	128.542	146.444	158.221

Table 7.15

US Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1 - 26/2/99	76.970	98.770	134.4903	140.455	143.865	98.794	182.298	200.306	211.471
1/1-31/5/99	95.667	99.629	97.89626	99.127	99.798	99.647	91.941	93.229	93.932
1/6 - 31/8/99	45.274	103.405	110.7889	112.031	112.707	103.363	103.828	104.615	105.150
1/9 - 30/11/99	68.177	97.975	98.36138	100.083	101.028	97.996	95.054	96.616	97.471
1/12-31/12/99	93.294	100.681	100.5222	100.693	100.785	100.682	100.610	100.777	100.868

Table 7.16

Gas Oil (O3) Hedge Efficiency For One Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1 -26/2/2000	100.000	128.559	121.651	124.954	126.794	143.327	39.825	37.740	36.713
1/1-31/5/2000	282.233	154.260	34.248	34.596	37.549	150.883	6.948	8.086	8.861
1/6 - 31/8/2000	98.234	97.048	76.676	73.439	71.819	96.797	94.483	88.926	94.158
1/9 - 30/11/2000	100.000	98.078	70.777	72.974	74.206	97.677	89.666	92.508	94.102
1/12-31/12/2000	100.945	100.038	102.363	102.535	102.627	99.951	92.556	93.358	93.637

Table 7.17

Oil Gas (O3) Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Costs'	
				0.116	0.178			0.116	0.178
1/1-27/2/1999	100.000	60.18	121.162	114.720	120.937	24.266	46.34513	41.246	38.313
2/3 -29/5/1999	100.000	100.133	88.530	84.432	83.419	100.133	101.799	97.990	96.887
1/6 - 31/8/1999	100.000	103.353	95.321	93.589	92.688	103.831	106.084	102.005	99.952
1/9- 30/11/1999	101.960	97.915	98.532	97.976	97.529	97.674	97.008	95.757	95.101
1/12/99-26/2/00	96.860	296.726	64.879	94.279	91.589	34.294	77.149	93.255	90.009
1/3-31/5/2000	282.233	186.119	128.059	123.426	121.085	167.801	508.892	219.789	164.636
1/6 -31/8/2000	98.234	96.527	65.1938	62.630	61.341	95.071	89.182	83.237	80.373
1/9 - 30/11/2000	100.000	97.395	101.563	105.322	107.447	96.854	91.684	100.798	106.455
1/12 - 31/12/00	100.945	100.052	102.360	102.620	102.671	100.004	100.151	100.491	100.672

Table 7.18

Cocoa Hedge Efficiency For Two Year Out-of-Sample Time Period

All figures are percentages

Contracts	Minimum Variance	GARCH 'Base'	GARCH 'Threshold'	GARCH 'Transaction Costs'		GARCH-X 'Base'	GARCH-X 'Threshold'	GARCH-X 'Transaction Cost'	
				0.116	0.178			0.116	0.178
1/1 - 27/2/1999	18.540	102.807	110.912	108.438	107.919	103.732	120.565	119.033	118.527
2/3 - 29/5/1999	89.984	101.266	101.727	101.729	101.388	100.840	102.935	103.042	102.829
1/6 - 31/8/1999	171.933	100.711	99.086	98.925	98.839	100.715	100.955	100.819	100.746
1/6 - 30/11/1999	14.570	100.265	100.127	99.867	99.729	99.785	102.270	102.093	101.999
1/12/99 - 26/2/00	0.116	98.848	97.833	97.383	97.222	99.783	101.014	100.867	100.737
1/3 -31/5/00	172.764	100.254	100.091	99.890	99.783	99.506	87.583	97.434	97.354
1/6-31/8/00	7.764	101.099	100.154	99.978	99.884	101.542	101.830	101.688	101.613
1/9- 30/11/00	19.682	99.739	100.589	100.449	100.374	100.044	102.224	102.132	102.084
1/12- 31/12/00	265.883	99.989	96.841	96.728	96.668	95.773	91.412	91.020	90.812

CHAPTER EIGHT

8.0 CONCLUSIONS.

The objective of this dissertation was to empirically investigate the hedging effectiveness of stock and commodity futures. Hedging effectiveness is compared across constant and time-varying hedge ratios. To achieve these objectives, the hedging effectiveness of commodity and stock index futures markets are investigated using alternative methods for estimating the hedge ratios. Overall evaluation of the results shows that the time-varying hedge ratios outperform the constant minimum variance hedge ratios in some cases but not all, while the time-varying hedge performs significantly better than an unhedged position in all cases. Hedging performance tests indicate that the risk reduction varies considerably from market to market and from one case to another. The evidence presented indicates that the hedging strategy using time-varying methods are superior to the constant methods for the stock index futures markets. Commodity markets results indicate that time-varying hedge methods are less effective in some cases than the constant minimum variance hedge ratio method. The application of two different out-of-sample test periods provides the opportunity to study the effects of different time periods on hedging effectiveness. In order to investigate the out-of-sample hedging effectiveness of the hedging methods under consideration, one and two years time periods were selected and parameters were estimated and applied to compute the hedge ratios and the portfolios for the two out-of-sample periods. Hedging effectiveness is then compared by comparing the variance of these portfolios and the change in the variance.

The effectiveness of four hedging methods and the unhedged method are applied for the commodity and stock index futures series. The traditional and minimum variance hedge ratios are constant, while the bivariate GARCH and the bivariate GARCH-X hedge ratios are time-varying. To avoid the problem of spurious regression and to check the stochastic structure of the data, ADF and KPSS unit root tests are conducted. Cointegration tests were applied to investigate the short run deviations from the long run relationship between the spot and futures price series. Every cash and futures prices of stock and commodity markets are found to be non-stationary in levels and stationary after first difference. Results from using the two step method of Engle-Granger (1987) and the Phillips and Hansen (1990) method show that all markets indicate a long-run cointegrated relationship between cash prices and futures prices. The short-run deviation from the cointegrating relationship is therefore a useful variable in modeling the conditional variance and the conditional mean of the series. One of the main contributions of the thesis is to investigate how the presence of cointegration between the spot and futures prices may affect the hedge ratio and the degree of hedging effectiveness. The error correction term from the cointegration test is applied in the GARCH-X model which is used to estimate the hedge ratio. The value of the hedge ratios estimated by the OLS method are less than unity for all stock markets. Meanwhile, the hedge ratios vary for the commodity markets in the within and out-of-sample time periods. The hedge ratios are less than one for O1, O3 and Cocoa, and close to one for O2 and Aluminum.

The effectiveness of different hedge ratios is evaluated by constructing portfolios implied by the computed ratios and then comparing the variance of these constructed portfolios. The comparison of changes in variance is conducted between the constant hedge ratios and the time-varying ratios. In the stock index futures markets, the GARCH portfolio reduces the variance by high percentages compared to both the unhedged and traditional portfolios. In comparison to the minimum variance hedge, the GARCH hedge ratio provides the lowest variance portfolio in Australia, Hong Kong and South Africa. The GARCH-X hedge ratio is highly effective compared to the unhedged and traditional methods in some cases. Among the time-varying hedge ratios, the GARCH-X model tends to marginally outperform the GARCH model. Therefore, the short-run deviation of a long-run cointegrated relationship between cash and futures prices for the stock markets improve the time-varying hedge ratio marginally when linked to the GARCH model.

The comparisons reveal that the dynamic hedging strategy based on the bivariate GARCH and GARCH-X estimation improves the hedging performance over the unhedged and traditional hedging strategy, while marginally improves the hedging performance in some cases in comparison to the minimum variance hedge methods for the stock markets. However, the minimum variance method outperforms the GARCH method in the Japan case for the one year out-of-sample period and in the UK and USA for the two year out-of-sample time periods. The GARCH model outperforms the minimum variance hedge method in the other cases for each time period. The GARCH-X method outperforms the unhedged methods and the traditional method in all cases. The GARCH-X method performs better than the minimum variance method in all cases except in Japan where the minimum variance model outperforms the GARCH-X marginally. I can conclude in general that the short run deviation between cash and futures prices has an important effect on hedging in the stock index futures markets involved. For the one year time period the GARCH-X outperforms the GARCH method in the cases of Australia, Germany, Japan, South Africa and USA, but slightly underperforms the GARCH model in the cases of Hong Kong and the UK. Hence the error correction term of short-run deviations from a long-run cointegrated relationship between cash and futures prices improves the time-varying hedge ratio when linked to the GARCH-X model. The percentage changes in variance are larger in the out-of-sample than the within-sample period. The hedged methods in the out-of-sample period show higher percentage change than the within-sample period in most cases. Reducing the length of the out-of-sample period does improve the performance of the time-varying hedge ratio in stock index futures. In practice, this implies that more frequent re-calibration for the time-varying methods based on the GARCH and GARCH-X, and the minimum variance model would lead to improved hedging effectiveness.

In the commodity markets, the reduction of portfolio variances using the standard GARCH model compared better to the unhedged method in all cases. The time-varying method reduces the variance by a high percentage compared to the unhedged method. The time-varying ratio reduces the variance compared to the traditional methods for the Aluminium, Cocoa and O3, but it underperforms in the cases of O1 and O2. In contrast to the stock markets, the GARCH method underperforms in all cases compared to the minimum variance method. It underperforms in the Aluminium and Cocoa cases by less than 1%. Meanwhile, the GARCH-X method outperforms some methods. For O1, the GARCH-X methods outperforms the unhedged method by 51.86%, but underperforms in comparison to the traditional, minimum variance and the GARCH method. The GARCH-X method underperforms in all cases in comparison to the minimum variance method, while it performs better in the Aluminum market. For both out-of-sample periods tested for commodity markets, the GARCH and GARCH-X methods reduce risk significantly compared to the unhedged and traditional hedge methods in most cases, while both methods underperformed compared to the minimum hedge methods. In the time-varying hedge ratio comparison, the GARCH-X model tends to marginally outperform the GARCH model. The comparisons reveal that the dynamic hedging strategy based on the bivariate GARCH and GARCH-X estimation improve the hedging performance over the unhedged and traditional hedging strategy, while marginally improving the hedging performance in some cases in comparison to the minimum variance hedge methods. The evidence is different to the stock markets, and less supportive of the use of the GARCH-X model.

A further important contribution of this thesis is to investigate the hedge efficiency of the time-varying hedge ratio in the presence of transactions costs. This is conducted by selecting the cases where the percentage change in variance for the out-of-sample time-varying hedge ratio estimated by GARCH and GARCH-X out-perform the constant minimum variance hedge ratio. Park and Switzer (1995) suggested less frequent re-balancing, such as re-balancing only when the optimal hedge ratio changes by at least a fixed minimum amount. This aspect is investigated in the thesis and has not been done in previous research.

The hedge efficiency for the selected cases of the out-of-sample time period varies from one case to another when applying the models involved. The GARCH and GARCH-X method produce hedge efficiency figures close to the ideal of 100%. Less frequent re-balancing and accounting for transaction costs both reduce hedge efficiency in almost all the cases investigated when compared to the constant minimum variance hedge method. Therefore, the general findings are that when the transaction costs are introduced, the hedge efficiency of the GARCH-X is not convincingly superior to the constant minimum variance hedge.

Overall, the role of hedging is important for both commodity and stock index futures markets as portfolio managers find the opportunity in these markets to decide on the appropriate market to hedge without the associated risk of adverse movements between markets. The empirical results in this study indicate that futures trading is a very effective means to significantly reduce the risk associated with a spot position especially in the stock index futures markets. The estimates of hedge ratios demonstrate that hedge ratios vary over time, with the implication that a dynamic hedging strategy may be appropriate in the futures markets. However, in advocating a dynamic hedging strategy it is necessary to take account of the additional costs which will arise from pursuing such a strategy. Hence, the portfolio manager must weigh up the trade off between the transaction cost and the benefits of reducing risk by adopting a dynamic hedging strategy. The small drop in variance for the commodity and stock markets advocates that the portfolio managers may opt for the constant minimum variance method instead of the standard GARCH or the

GARCH-X model as the transaction cost may be too high for the time-varying methods. However, portfolio managers may hedge their position using the GARCH or GARCH-X method instead of the unhedged and traditional methods, where the drop in variances are big. One important feature of all within and out-of-sample results is the evidence that it is advisable to hedge a position in all commodity and stock markets rather than remain unhedged. Selecting the optimal hedging strategy varies across the markets studied.

Myers (1991) and Baillie and Myers (1991) find no risk reduction with use of time-varying hedge ratios in the wheat and gold futures markets, respectively. Similarly in this thesis, the time-varying method underperforms compared to the minimum variance method for commodity markets. Park and Switzer (1995) found both within-sample and out-of-sample evidence to indicate that a hedging strategy using the bivariate GARCH method is potentially superior to the constant methods. Thus, the commodity and stock futures contracts involved in this study may give portfolio managers a valuable instrument by which to avoid risk at times without liquidating their spot position. The results presented advocate further research in this field. Future research may be conducted using different markets, data frequency and different time periods. Other application of the methods used for estimation of optimal hedge ratios also remains a question for future research.

REFERENCES.

Abhyankar, A. (1995) "Return and Volatility Dynamics in the FTSE-100 Stock Index and Stock Index Futures Markets," Journal of Futures Markets, 15, 457-488.

Anderson, R. W. and Danthine, J. P. (1981) "Cross Hedging," Journal of Political Economy, 89, (6), 1182-1196.

Baillie, R. T. and Myers, R. J. (1991) "Bivariate GARCH Estimation of the Optimal Commodity Futures Hedge," Journal of Applied Econometrics, 6, (2), 109-124.

Banerjee, A. Dolado, J. J. Hendry, D. F and Smith, G. W. (1986) "Exploring Equilibrium Relationships in Econometrics Through Static Models: Some Monte Carlo Evidence," Oxford Bulletin of Economics and Statistics, 48, 253-278.

Bank of Japan (1999) "Stagnation and Structural Adjustments of Nonmanufacturing Industries during the 1990s". Research and Statistics Department. Research Papers.

Bell, D. E. and Krasker, W. S. (1986) "Estimating Hedge Ratios," Financial Management, 15, (2), 34-39.

Berndt, E., Hall. B., Hall. R., and Hausman. J. (1974) "Estimation and Inference in Nonlinear Structural Models," Annals of Economic and Social Measurement, 3, 653-665.

Blake, D. (2000) "Financial Market Analysis" McGraw-Hill Book Company Europe.

Boettcher, C., Merholz, G. and Roesler, M. (2001) "Matieres Premieres Agricoles" (Café, Cacao, Brent Crude Oil). Gestion de Portefeuille et des Risques 1. CERAM ESC-MIM2

Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroskedasticity," Journal of Econometrics, 31, 307-327.

Bollerslev, T., Chou. R., and Kroner. K. (1992) "ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence," Journal of Econometrics, 52, 5-59.

Butterworth, D. and Holmes, P. (1997) "The Hedging Effectiveness of Stock Index Futures: Evidence for The FTSE-100 and FTSE-MID250 Indexes," University of Durham, Department of Economics, Working Paper No: 01-31.

Caner, M. and Kilian, L. (2001) "Size Distortion of Tests of the Null Hypothesis of Stationarity: Evidence and Implication for the PPP Debate" Journal of International Money and Finance, 20, 639-657.

Castelino, M. G. (1992) " Hedging Effectiveness: Basis Risk and Minimum-Variance Hedging," Journal of Futures Markets, 12, (2), 187-201.

Cecchetti, S. G, Cumby, R. E, and Figlewski, S (1988) "Estimation of the Optimal Futures Hedge," Review of Economics and Statistics, 70, (4), 39-623.

Chan, K. (1992) "A Further Analysis of the Lead-Lag Relationship between the Cash Market and the Index Futures Market," Review of Financial Studies, 5, (1), 123-153.

Chou, R. (1988) "Volatility Persistence and Stock Valuation: Some Empirical Evidence Using GARCH," Journal of Applied Econometrics, 3, 279-294.

Choudhry, T. (1997) "Short-Run Deviation and Volatility in Spot and Futures Stock Returns: Evidence from Australia, Hong Kong and Japan" Journal of Futures Markets, 17, (6), 689-705.

Choudhry, T. (1999) "Time-Varying Distribution and Hedging Effectiveness of Three Pacific-Basin Stock Futures," University of Southampton Working Paper.

Clark, P. K. (1973) "A Subordinate Stochastic Process Model with Finite Variance for Speculative Prices," Econometrica, 41, 125-155.

Crowder, W. J and Hamed, A. (1993) "A Cointegration Test for Oil Futures Market Efficiency," Journal of Futures Markets, 13, (8), 933-941.

Dickey, D. A. and Fuller, W. A (1979) "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," Journal of the American Statistical Association, 74, 427-31.

Directorate-General for Economic and Financial Affairs (2002) "Germany's Growth Performance in the 1990's". European Economy, European Commission. Economic Papers

Duffie, D. (1989) Futures Markets, Prentice Hall, Englewood Cliffe, New Jersey.

Ederington, L. H. (1979) "The Hedging Performance of The New Futures Markets," Journal of Finance, 34, (1), 157-170.

Edwards, F., and Park, J. (1996) "Do Managed Futures Make Good Investments? The Journal of Futures Markets, 16, 475-517.

Enders, W. (1995) "Applied Economic Time Series" New York. Wiley.

Engle, R. F. (1982) "Autoregressive Conditional Heteroscedasity with Estimation of the Variance of United Kingdom Inflation," Econometrica, 50, 987-1008.

Engle, R. F and Bollerslev, T. (1986) "Modelling the Persistence of Conditional Variances," Econometric Reviews, 5, 1-50, 81-87.

Engle, R. F. and Granger. C. W. J. (1987) "Cointegration and Error Correction: Representation, Estimation and Testing," Econometrica, 55, 251-276.

Engle, R. and Kroner, K (1995) "Multivariate Simultaneous Generalized ARCH," Econometric

Theory, 11, 122-150.

Engle, R. F. and Yoo, B. S. (1987) "Forecasting and Testing in Cointegrated Systems," Journal of Econometrics, 35, 143-159.

Fama, E. (1965) "The Behaviour of Stock Market Prices," Journal of Business, 38, 34-105.

Figlewski, S. (1984) "Hedging Performance and Basis Risk in Stock Index Futures," Journal of Finance, 39, 657-669.

Figlewski, S. (1985) "Hedging with Stock Index Futures: Theory and Application in a New Market," Journal of Futures Markets, 5, 183-199.

Fleming, J., Ostdiek, B, and Whaley, R. E (1996) Trading cost and the Relative Rate of Price Discivery in Stock, Futures, and Option Markets. The Journal of Futures Markets, Vol. 16, No 4, 353-387.

Fortune, P. (1989) "An Assessment of Financial Market Volatility: Bills, Bonds, and Stocks," New England Economic Review, Federal Reserve Bank of Boston, 13-28.

Garman, M. and Klass, M. (1980) "On the Estimation of Security Price Volatilities from Historical Data," Journal of Business, 53, 67-78.

Gay, G. D, and Jung, J .D. (1999) "A Further Look at Transaction Cost, Short Sale Restrictions and Futures Markets Efficiency: The Case of Korean Stock Index Futures", Journal of Futures Markets, Vol 19, 4, 153-174.

Giannopoulos, K. (1995) "Estimating the Time Varying Components of International Stock Markets Risk," European Journal of Finance, 1, 129-164.

Gizycki, M. and Lowe, P. (2000) "The Australian Financial System in the 1990s". Reserve Bank of Australia Research Discussion Paper,181-215.

Hansen, B. E. (1992) "Efficiency Estimation and Testing of Cointegration Vectors in the Present of Deterministic Trends," Journal of Econometrics, 53, 87-1121.

Harris, R. I. D. (1995) "Using Cointegration Analysis in Econometric Modelling," Prentice Hall. Harvester Wheatsheaf.

Holland, A, and Vila, A. F. (1997) "Features of a Successful Contract: Financial Futures On LIFFE", Bank of England Quarterly Bulletin, 181-186.

Holmes, P (1996) "Stock Index Futures Hedging: Hedge Ratio Estimation, Duration Effects, Expiration Effects and Hedge Ratio Stability," Journal of Business Finance & Accounting, 23, (1), 63-77.

Howard, C. T. and D'Antonio, L.J (1991) "Multiperiod Hedging Using Futures: A Risk

Minimisation Approach in the Presence of Autocorrelation," Journal of Futures Markets, 11, (2), 697-710.

Jensen, G. R, Johnson, R. R, and Mercer, J. M. (2000) " Efficient Use of Commodity Futures in Diversified Portfolio," The Journal of Futures Markets, 20, (5), 489-506.

Johnson, L. L. (1960) "The Theory of Hedging and Speculation in Commodity Futures," Review of Economic Studies, 27, 139-151.

Junkus, J. C and Lee, C.F. (1985) "Use of Three Stock Index Futures in Hedging Decisions," Journal of Futures Markets, 5, (2), 201-222.

Kawaller, I.G., Kock, P.D., and Kock, T.W. (1990) "Interday Relationship Between Volatility in S&P500 Futures Prices and Volatility in the S&P Index," Journal of Banking and Finance, 14, (2/3), 373-397.

Keynes, J. M. (1930) "A Treatise on Money, Volume Two- The Applied Theory of Money," Macmillan, London.

Kim, K. A, Szakkmay. A. C, and Schwarz, T. V. (1999) "Trading Costs and Price Discovery Across stock Index futures and Cash Markets," Journal of Futures Markets, 19, (4), 475-498.

Kling, A. (1986) "Futures Markets and Transactions Costs". In Financial Futures and Options in the US Economy: A Study by the Staff of the Federal Reserve System, edited by M.L. Kwast, Board of Governors of the Federal Reserve System, Washington, 41-54.

Krehbiel, T. and Adkins, L. C. (1993) "Cointegration Test of The Unbiased Expectations Hypothesis in Metal Markets," Journal of Futures Markets, 13, (7), 753-763.

Krapels, E. N, and Pratt, M. (1998) "Crude Oil Hedging: Bench Marking Price Protection Strategies", Energy Security Analysis, Inc. Energy & Power Special Reports. Risk Books.

Kwaitkowski, D, Phillips, P. C. B, Schmidt, P, and Shin, Y. (1992) "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?," Journal of Econometrics, 54, 159-178.

Lee, D. and Schmidt, P. (1996) "On the Power of the KPSS Test of Stationary against Fractionally-Integrated Alternatives," Journal of Econometrics, 73, 285-302.

Lee, S. H. and Amsler, C. (1997) "Consistency of the KPSS Unit Root Test Against Fractionally Integrated Alternative," Economics Letters, 55, 151-160.

Lee, Tae-Hwy (1994) "Spread and Volatility in Spot and Forward Exchange Rates," Journal of International Money and Finance, 13, (3), 375-383.

Leeson, N. (1996) "Rogue Trader," with Edward Whitley. London: Little, Brown.

Lence, S. H. (1995) "On the Optimal Hedge Under Unbiased Futures Markets," Economics Letters, 47, 385-388.

Lindahl, M. (1989) "Measuring Hedging Effectiveness with R^2: A Note," Journal of Futures Markets, 9, 469-475.

Lindahl, M. (1992) "Minimum Variance Hedge Ratio for Stock Index Futures: Duration and Expiration Effect," Journal of Futures Markets, 12, (1), 33-53.

Luintel, K. B. (2001) "Heterogeneous Panel Unit Root Tests and Purchasing Power Parity" The Manchester School Supplement, 69, 42-56.

Maddala, G. S. (1992) "Introduction to Economics," Second Edition. New York: Macmillan.

Maddala, G. S, and Kim, I. (1998) "Unit Roots, Cointegration, and Structural Change," Cambridge University Press.

Mandelbrot, B., (1963) "The Variance of Certain Speculative Prices," Journal of Business, 36, 394-419.

Moschini, G. and Myers, R. J. (2002) "Testing for Constant Hedge Ratios in Commodity Markets: A Multivariate GARCH Approach", Journal of Empirical Finance, 9, 589-603.

Myers, R. J. (1991) "Estimating Time-Varying Optimal Ratios on Futures Markets," Journal of Futures Markets, 11, (1), 39-53.

Myers, R. J. and Thompson, S. R (1989) "Generalised Optimal Hedge Ratio Estimation," American Journal of Agricultural Economics, 71, (4), 858-868.

Nabeya, S. and Tanaka, K. (1988) "Asymptotic Theory of a Test for the Constancy of Regression Coefficient Against the Random Walk Alternative," Annals of Statistics, 16, 218-235.

Nankervis, J. C. and Savin, N. E., (1985) "Testing the Autoregressive Parameter with the t-statistics," Journal of Econometrics, 27, 143-162.

Officer, R. (1973) "The Variability of the Market Factor of the New York Stock Exchange," Journal of Business, 46, 434-453.

Pagan, A. R. and Wickens, M. R. (1989) "A Survey of Some Recent Econometrics Methods," Economic Journal, 99, 962-1025.

Park, T. H. and Switzer, L. N. (1995) "Bivariate GARCH Estimation of the Optimal Hedge for Stock Index Futures: A Note," Journal of Futures Markets, 15, (1), 61-67.

Parkinson, M. (1980) "The Extreme Value Method For Estimating the Variance of the Rate of Return," Journal of Business, 53, 61-65.

Pesaran, M. H and Pesaran, B. (1997) "Working with Microfit 4.0: Interactive Econometric Analysis", Oxford University Press.

Phillips, P. C. B. and Hansen, B. E. (1990) "Statistical Inference in Instrumental Variables Regression with I(1) Processes," Review of Economic Studies, 57, 99-125.

Phillips, P. C. B and Loretan, M. (1991) "Estimating Long-Run Economic Equilibria", Review of Economic Studies, 58, 407-436.

Pizzi. M. A, Economopoulos. A. J, and O'Neill (1998) "An Examination of The Relationship between Stock Index Cash and Futures Markets: A Cointegration Approach," Journal of Futures Markets, 18, (3), 297-305.

Poterba, J., and Summers, L. (1986) "The Persistence of Volatility and Stock Market Fluctuation," American Economic Review, 76, 1142-1151.

Rutledge, D. J. S. (1972) "Hedgers Demand for Futures Contracts: A Theoretical Framework with Applications to the United States Soybean Complex," Food Research Institutes Studies, 11, 237-256.

Scholes, M., and Williams, J. (1977) "Estimating Betas from Nonsynchronous Data," Journal of Financial Economics, 5, 309-328.

Schwarz, T. V. and Szakmary, A. C. (1994) "Price Discovery in Petroleum Markets: Arbitrage, Cointegration, and The Time Interval of Analysis," Journal of Futures Markets, 14, (2), 147-167.

Shalen, C.T. (1989) "The Optimal Maturity of Hedges and Participation of Hedgers in Futures and Forward Markets," Journal of Futures Markets, 9, (3), 215-224.

Sims, C. A (1980) "Macroeconomics and Reality," Econometrica , 48, 1-48.

Stein, J. L. (1961) "The Simultaneous Determination of Spot and Futures Prices," American Economic Review, 51, (5), 1012-1025.

Stoll, H.R., and Whaley, R.E. (1990) "The Dynamics of Stock Index and Stock Index Futures Returns," Journal of Financial and Quantitative Analysis, 25, (4), 441-468.

Sutcliffe, C. (1997) Stock Index Futures, Second Edition. International Thomson Business Press, London.

Telser, L. G and H.N Higinbotham (1977) "Organized Futures Markets: Costs and Benefits," Journal of Political Economy, 85, 969-1000.

Timmermann, A. (1995) "Volatility Clustering and Mean Reversion of Stock Returns in an Asset Pricing Model with Incomplete Learning," UCSD, Department of Economics, Discussion Paper, 95-23.

Viswanath, P. V. (1993) "Efficient Use of Information, Convergence Adjustments, and

Regression Estimates of Hedge Ratios," Journal of Futures Markets, 13, (1), 43-53.

Wahab, W. (1995) "Conditional Dynamics and Optimal Spreading in Precious Metals Futures Markets," Journal of Futures Markets, 15, (2), 131-166.

Wang, G. H. K, Yau, J., and Baptiste, T. (1997) "Trading Volume and Transaction Costs in Futures Markets", Journal of Futures Markets, 17, (7), 757-780.

Witt, H. J., Schroeder. T. C., and Hayenga, M. L. (1987) "Comparison of Analytical Approaches for Estimating Hedge Ratios for Agricultural Commodities," Journal of Futures Markets, 7, 135-146.

Working, H. (1953) "Futures Trading and Hedging," American Economic Review, 43, (3), 314-343.

Yadav, P.K. and Pope, P. F. (1994) "Stock Index Futures Mis-pricing: Profit Opportunities or Risk Premia?" Journal of Banking and Finance, 18, 921-953.