The hedging effectiveness of single stock futures:
A study using constant and time-varying
hedge ratios under GARCH modeling

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ABSTRACT

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This study investigates the hedging effectiveness of Universal Stock Futures trading in London at protecting the underlying spot position from variations in portfolio returns using four different hedge ratios. The hedge ratios under analysis are: the naive 1:1 hedge ratio, the risk-minimizing hedge ratio, a modified version of the risk-minimizing hedge ratio and a time-varying hedge ratio under a GARCH (1,1) process which is allowed to change on a daily basis. The aim of the research is to examine which hedge ratio provides the best protection from market fluctuations when hedging a stock spot position with its futures contract. The findings suggest that the time-varying hedge ratio provides a better hedging strategy than the other techniques although some companies exhibited a smaller portfolio variance when protected with a constant hedge ratio.

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1. INTRODUCTION

1.1 Overview of single stock futures

Stock futures contracts are financial instruments that have only recently been inaugurated on the world's major Derivatives Exchanges such as Euronext/LIFFE in Europe and OneChicago in the United States. Their widespread introduction has been the most widely anticipated event since the introduction of stock index futures contracts in 1982. Indeed, The Center for the Study of Financial Innovation has dubbed this new financial product the "Ultimate derivative" and many experts claim that stock futures have the potential to revolutionize the way equities are traded in the marketplace.[1] However, despite the wave of optimism that this new product generated prior to its introduction in the United States, the trading volume has not reached experts' expectations mainly because of the lack of acceptance that the institutional sector has given the instrument. The various exchanges are presently working to develop the necessary knowledge of the contracts by the different market players in order to promote its successful implementation in the marketplace. [2]

Stock futures are standardized contracts written on shares of individual companies which give the purchaser (seller) the obligation, upon expiration, to buy (sell) a specific number of shares of the underlying stock at a specific price determined on the date of the purchase (sale).

[1] Faille, C. (2002). The ultimate derivative for an equity culture. Daily News; White Plains; Feb.21st 2002.
[2] Zwick, S. & Collins, D.P. (2004). One year in and the jury is still out. Futures, 33, 66-69.

Although some contracts require physical delivery, a majority of transactions usually settle in cash before expiration. Furthermore, there are three different strategies that an investor can utilize in order to manage the expiration of a contract. As previously mentioned, the investor could offset the position by taking the opposite side of the initial transaction prior to expiry effectively eliminating the obligation to buy (sell) the shares at the end of the contract. Also, the investor could hold the contract until expiry and fulfill the obligation by taking (making) delivery of the shares or by cash settling the difference between the spot price and the settlement price. Finally, the investor could roll over the position into a later contract thereby delaying the expiration of the strategy until a later date. This last plan is achieved by offsetting the present position and entering into a new position with a subsequent expiration.

When a position is entered into, there is no immediate exchange of cash or goods as this exchange is deferred until the expiration of the contract. Therefore, a margin deposit is required as long as the position remains open, as evidence of the investor's financial ability to complete the transaction. This margin is the amount of cash and cash-equivalent securities that an investor must maintain in a futures or margin account and is established by each Exchange varying between contracts according to the volatility of the underlying asset. Generally, the initial margin will be approximately 20% of the value of the position.[3] However, it may be lower when certain futures strategies are employed or when an offsetting position in stock options or the spot market exists.

[3] OneChicago website

With a stock futures transaction, the investor makes a legally binding promise to buy or sell the underlying stock in the future. Consequently, the investor does not become an owner of the corporation, as with a stock purchase, and will not receive dividends, voting rights and all other privileges associated with share ownership. Therefore, a stock futures price should correspond to the cost of buying the shares on the spot market and holding them for the life of the futures contract. If the price does not equate to that definition, an arbitrageur could make a profit by transacting in the spot and the futures markets accordingly. Hence, the price of the futures is generally based on the following formula:

Futures price = stock price x (1 + annualized interest rate) – PV of dividends (1)

According to the above formula, the price of the futures depends on the following elements: the price of the underlying share, the interest earned on the capital that should have been used to purchase the shares on the spot market and the dividends that should have been earned over the life of the futures contract. Consequently, the futures will trade at a premium relative to the stock price since interest should be earned on the capital that was not allocated to purchase the full value of the shares. However, the futures price will be adjusted downward by the present value of the expected dividends during the life of the contract since as mentioned previously, the holder will not be entitled to collect those dividends. Therefore, when a large dividend amount is expected, the futures price may trade at a discount to the stock price. Since different investors have divergent expectations about future interest and dividend rates, the market will experience fluctuations in futures prices.

1.2 Exchanges on which single stock futures trade

At the present time, stock futures are traded on many Exchanges throughout the world. However, three major organizations where these instruments are traded will be discussed. They are: The Euronext/LIFFE joint venture in London England, The OneChicago Exchange in Chicago USA and The Sydney Futures Exchange in Sydney Australia.

Euronext/LIFFE: The contracts began trading on the Euronext/LIFFE in London on January 29th 2001 where they are called Universal Stock Futures. The Euronext/LIFFE exchange is an alliance of the major European Derivatives Exchanges and the largest futures exchange in the world. More than 100 companies spanning eleven countries have Universal Stock Futures trading on their shares including: Danone Group, L'Oréal, Unilever, DaimslerChrysler, Crédit Suisse Group and many more. On Euronext, the contracts are called Universal Stock Futures and they are based on 1,000 shares for UK & Italian shares and 100 shares for other European and US stocks. Upon expiration, the futures contracts are usually cash-settled although some contracts require physical delivery (mostly in Scandinavian countries). The last trading day varies according to the country of origin. However, it is generally the third Friday of the expiry month and the settlement day is the following business day. The contract months are the two nearest expirations of the trading cycle (March, June, September, December) in addition to the two nearest serial months. The margin required is usually 10% to 15% of the value of the underlying shares. It should be noted that since Universal Stock Futures are based on shares trading in various countries, each country with its own regulatory body, there are several differences regarding contract specifications depending on the country where the underlying shares originate.

OneChicago: In December 2000, the advent of stock futures overseas pushed the American government into allowing their negotiation in the United States in order to ensure that trading revenues would not be lost to foreign competition. As a consequence, the OneChicago Exchange, a joint venture of the three exchanges based in Chicago: The Chicago Mercantile Exchange (CME), the Chicago Board Options Exchange (CBOE) and the Chicago Board of Trade (CBOT), was created. On November 8th 2002, trading of Single-Stock Futures began on some of the largest American companies including: AOL Time Warner Inc., AT&T Corporation, IBM, Microsoft Corp. and Procter&Gamble. Overall, more than 100 companies are trading on that exchange. On OneChicago, the contracts are called Single-Stock Futures and they are based on 100 shares of the underlying stock. Upon expiration, physical delivery is required. The last trading day is the third Friday of the settlement month and the settlement day is the third business day following the expiration day. The contract months are the two nearest expirations of the trading cycle (March, June, September, December) in addition to the two nearest serial months. This ensures that a total of four expirations per contract are always trading. The margin required is usually 20% of the position value.

Sydney Futures Exchange: Stock futures started trading in Australia on the Sydney Futures Exchange in May 1994. They are called Individual Share Futures and are usually based on 1000 shares of Australia's largest stocks such as: News Corporation, Telstra, BHP and the National Australia Bank. Upon expiration, physical delivery is required. The last trading day is the last Thursday of the settlement month and the settlement day is the following business day. The contracts trade according to a four-month trading cycle and the margin required is usually between 2% and 20% of the value of the position.

1.3 Advantages and disadvantages of single stock futures

Stock Futures offer many opportunities and advantages with regards to the performance of a portfolio of shares. Indeed, they can greatly increase the effectiveness with which the manager can hedge against adverse movements in the stock market and also enable the manager to benefit from market timing opportunities at a relatively low cost compared to a strategy that would require the direct purchase of shares. Following are some of the advantages and disadvantages offered by stock futures.

Cost effectiveness: Stock Futures are inexpensive to trade and offer a cheap alternative to investing in the stock market. Indeed, since they are usually cash settled, they do not have the commissions and fees associated with the transaction of actual shares. Since commissions are usually smaller for futures than for stocks and market makers provide tighter bid-ask spreads, they represent a lower cost strategy to investing in the stock market.

Increased leverage: The capital required to trade futures is lower through a minimal margin deposit relative to the full amount required for a stock purchase. Therefore, they provide a capital-efficient way of investing in the stock market. This greater leverage may provide greater profits or losses depending on the movements of the markets. Indeed, an investor effectively gets exposure to a stock equivalent to many multiples of the initial capital outlay. Therefore, the gains and losses will be greater than if the shares had been acquired on the spot market.

Opportunity to benefit from movements of the market: The Futures contracts enable a speculator to gain exposure to the price movements of a single stock without having to buy or short sell the shares in the spot market. They also enable the investor to switch the exposure from one stock to another without the large costs associated with such a transaction in the spot market and without having to change the composition of the underlying stock portfolio.

Insurance against adverse movements of the market: Stock futures provide hedgers with specific insurance against adverse price movements of a particular underlying stock since any decline in the value of the shares is offset by an increase in the value of the futures.

No short selling restrictions: Stock futures purchases do not have the costs and administrative inconveniences associated with borrowing shares and short selling them in the market. Also, investors no longer have to take into account the uptick rule which prevents a short seller from shorting a stock that experienced a previous drop in price.

Basis or Arbitrage trading: Arbitrageurs are able to do Basis or Arbitrage trading on this new product and therefore, increase their revenues.

1.4 Investment strategies using single stock futures

Diversification is essential to sound portfolio management. It should be designed to increase returns and/or reduce the risk of the portfolio. The use of stock futures enables the manager to effectively protect the portfolio from large fluctuations in its returns and provides a more stable expected revenue. Following are some of the strategies that may be implemented with the use of stock futures.

Delayed ownership: An investor could use stock futures as an inexpensive alternative for purchasing the shares of a company in the future at a predetermined price. Under this strategy, upon the expiration of the contract, the investor would take delivery of the underlying shares to augment the portfolio.

Basic hedging: An investor may foresee a future short term drop in the price of a stock currently owned. Therefore, instead of selling the shares, the investor could sell stock futures on them effectively hedging his position in that particular stock while leaving the equity portion of the portfolio intact. With this strategy the targeted stock is protected against a decrease in its value while the rights associated with the ownership of the shares are kept. Moreover, the losses incurred by the decrease in the shares' price are offset by the gains made on the stock futures position.

Long or short directional trades: Stock futures could be used to invest in equities that are expected to do better in the short term than an investor's current stock portfolio. In addition, the investor could take advantage of an expected drop in a particular stock price by selling stock futures on that stock and buying back the contracts at a later time when the futures price has decreased accordingly.

Index hedging: When an investor owns a broad-based index investment in the S&P 500 or another benchmark, stock futures could be used to momentarily remove a particular stock from the portfolio by selling futures contracts on the number of shares owned.

Pairs trading: If the investor believes that a particular stock will outperform that of a competitor, stock futures on the shares of the outperformer could be purchased while the stock futures of the underperformer are simultaneously sold. This strategy enables the investor to custom-build the exposure of the portfolio according to the expected performance of the two companies without affecting the exposure of the portfolio to the broader market or sector performance.

"Portable alpha" trading: When a portfolio manager faces an earnings announcement or another volatility triggering event for one of the stocks under management, instead of selling an index futures contract and foregoing the improvement in the index due to the good performance of the market in general, the manager could sell a stock futures contract on that specific stock effectively hedging only the performance of that stock.

Counteract selling restrictions: If a company's prospectus prevents buyers of its shares from selling their stock for a certain period of time or if the shares are purchased in a plan that prevents the sale of shares, the investor could sell stock futures to hedge the exposure to the stock until the restrictive period ends.

1.5 Objectives of the research

Several comments are presently being made about the impact that stock futures have on the trading environment of the world's larger stock markets. Some experts say that stock futures are less expensive and easier to use in hedging equity risk than alternatives such as stock index futures or stock options.[4] However, are they as good a hedge as other derivatives? Moreover, which hedging strategy should an investor use in order to achieve the maximum effectiveness of these new products. These are all issues that researchers should attempt to resolve. Consequently, my thesis project will try and resolve the latter question by studying the hedging effectiveness of stock futures when using the naive 1:1 hedge ratio, the risk-minimizing hedge ratio, a modified version of the risk-minimizing hedge ratio and a time-varying hedge ratio. The naive hedge ratio essentially equals one for the duration of the hedging period. The risk-minimizing hedge ratio is calculated via an ordinary least squares regression of the spot asset returns on the futures returns and remains constant for the period under study. The modified risk-minimizing hedge ratio adds a correction for the serial correlation of the regression's residuals. Finally, the time-varying hedge ratio changes on a daily basis and is computed via a bivariate GARCH (1,1) process.

1.6 Importance of the research

The more volatile markets become, the more demand there will be for hedging instruments such as stock futures. The question of which hedging strategy provides the greater risk reduction is important since the rationale for introducing this product was mostly to increase the ease and effectiveness with which one could hedge a spot position. Therefore, empirically testing the hedging efficiency of different hedging techniques utilizing stock futures is relevant in order to assess whether this instrument is as big a revolution as experts claim. Also, the advent of this new product on the American market and its trading success should in the end impel the Montreal Exchange to start permanently trading stock futures on Canadian stocks. A study of the hedging effectiveness of stock futures could therefore help determine whether introducing this derivative on the Canadian market is worth the effort.

The remainder of the thesis is organized as follows: Section 2 reviews the relevant literature on the subject of hedge ratios and their hedging effectiveness, Section 3 introduces the methodology and the various hedge ratios used for the study, Section 4 describes the data used to conduct the research, Section 5 presents the empirical results and the diagnostic tests, Section 6 compares the hedging effectiveness of each strategy and finally, Section 7 concludes.

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[4] Wright, E. M. (2002). Waiting on the futures: single-stock futures will offer managers the opportunity to increase their leverage, but the downside is the possibility of more risk. Financial Planning; New York; April 1st 2002.

2. LITERATURE REVIEW

2.1 Impact of single stock futures on the spot market

Because single stock futures have only recently started to trade on recognized exchanges, previous research covering this new product is very limited and restricted to its impact on the volatility and trading volume of the underlying spot market. Lee and Tong (1998) found that the volatility of the Australian stock market had not increased following the introduction of single-stock futures while the trading volume of the underlying shares had risen significantly thereby enhancing liquidity in the market. Also, like their predecessors, Dennis and Sim (1999) showed that in the Australian market, single stock futures had not increased the volatility of the underlying stocks.

2.2 Hedging effectiveness of currency and stock index futures

Although to my knowledge, no work has been published on the hedging effectiveness of single stock futures, several studies pertaining to the hedging efficiency of currency and stock index futures may provide a good background for the thesis. Chang and Shanker (1986) compared the hedging effectiveness of currency futures versus currency options using a modified version of the Howard and D'Antonio method (1984) which takes into account transaction costs and margin requirements. They found that currency futures were a better hedge than currency options. Lien and Tse (2001) also compared the hedging effectiveness of currency futures versus options but used the lower partial moments method to conduct their study. They also came to the conclusion that futures were a better hedging instrument than options. Gagnon et al. (1998) studied the hedging effectiveness as well as the utility maximization of hedging currency risk in the futures market. They found that using a trivariate GARCH (1,1) process yielded a significant reduction in the risk and greater utility of portfolios compared to a static minimum-variance hedge ratio approach. Gagnon and Lypny (1994) assessed the hedging effectiveness of the Toronto 35 Index futures using a dynamic strategy with the application of a bivariate GARCH (1,1) process and found that the product significantly reduced risk both in-sample and out-of-sample compared to static hedging strategies such as a naive or constant hedge. Butterworth and Holmes (2001) contrasted the hedging efficiency of the new mini FTSE mid 250 stock index futures versus the broader FTSE-100 futures and found the smaller index futures more effective at hedging an actual diversified portfolio. They concluded that the hedging efficiency of the FTSE-100 futures contract might have been overstated in the past since it is usually based on portfolios mimicking the broad market index. Kroner and Sultan (1993) improved on conventional hedging models such as the OLS regression which yields the risk-minimizing hedge ratio by taking into account the stochastic nature of return distributions and the cointegration of asset prices. They elaborated on a conditional hedging model to compute the risk-minimizing hedge ratio and found that both in-sample and out-of-sample portfolio variances were reduced. Also, they constructed a dynamic hedging strategy where portfolio rebalancing occurred when utility gains were superior to the transaction costs incurred. They concluded that the conditional hedging model was better than the conventional strategy even when transaction costs were included in the analysis. Finally, Brailsford, Corrigan and Heany (2001) performed an empirical study of three measures of hedging efficiency: The portfolio S.D. Ranking, the Howard and D'Antonio measure and the Lindhal measure. Their results suggest that the level of hedging effectiveness is sensitive to the method used in the study.

2.3 Optimal hedge ratios

Many different hedge ratios are employed in the literature as well as in practice and finding the optimal hedge ratio has been a concern for many researchers. Lypny and Powalla (1998) made a comparison between dynamic and constant hedging techniques and showed that a dynamic strategy using a GARCH covariance structure combined with an error correction for the mean returns yielded significant in and out-of-sample improvements over constant hedge ratios. Chakraborty and Barkoulas (1999) conducted their own comparison of the performance of dynamic time-varying versus static or constant optimal hedge ratios on five currencies. Their evidence supports the use of time-varying optimal hedge ratios. However, their model provides superior out-of-sample performance for only one of the five currencies studied. Chen et al. (2003) produced a detailed review of the different hedge ratios suggested by the literature and the different approaches which can be used in estimating them. They came to the conclusion that unless investors are infinitely risk averse, that the futures and spot prices are jointly normally distributed and that futures prices follow a pure martingale process, the different techniques will lead to divergent estimations of the optimal hedge ratio. Choudhry (2003) compared the hedging effectiveness of four different hedge ratios: The traditional hedge, the minimum-variance hedge, the bivariate GARCH and the GARCH-X hedge ratios on six different stock markets. His results suggest that the time-varying hedge ratios outperform the constant type but not in all situations. Miffre (2004) presents a new hedge ratio: The conditional OLS Minimum Variance Hedge Ratio which incorporates the effect of past information into the standard OLS Minimum Variance hedge ratio thereby making it time-dependent. She compared this approach with the naive 1:1 hedge, the roll over standard OLS hedge and the bivariate GARCH (1,1) hedge. She found that this new method outperformed the other three approaches.

3. METHODOLOGY

3.1 Hedge ratios used in the study

In this thesis, the hedging effectiveness of single stock futures will be analyzed using three different hedge ratios broadly employed in the literature and in practice: the naive 1:1 hedge ratio, the risk-minimizing hedge ratio and a time-varying hedging strategy based on the GARCH (1,1) process. In addition, a fourth technique namely the modified risk-minimizing hedge ratio will be evaluated. This last strategy corrects the basic risk-minimizing hedge ratio for serial correlation in the residuals through a Hildreth-Lu procedure. The naive, risk-minimizing and modified risk-minimizing measures are constant hedge ratios which do not vary over the hedging period. The last method is a dynamic strategy which yields an updated hedge ratio on a daily basis. Therefore, the hedging portion of the portfolio is reassessed daily and adjusted accordingly. Furthermore, in order to hedge a portfolio of spot positions, one must offset their underlying risk by entering into the opposite side of the transaction with the appropriate number of futures contracts dictated by the hedge ratio. Consequently, the portfolio return can be represented by the following equation:

$$\mathbf{R_{p,t} = r_{s,t} - \beta_t \, r_{f,t}} \qquad \textbf{(2)}$$

Where $R_{p,t}$ is the return on the portfolio, $r_{s,t}$ is the return on the spot asset, β_t is the hedge ratio and $r_{f,t}$ is the return on the futures instrument.

3.2 The naive 1:1 hedge ratio

This first measure is widely used in practice. Under this strategy, the underlying portfolio is hedged using the number of futures contracts which exactly cover the number of shares to be protected. Therefore, the hedge ratio always equals one. Two main problems exist with this approach. First, it does not take into account the fact that the spot and the futures markets are not perfectly correlated and second, it does not recognize the stochastic nature of both markets and therefore the fact that the optimal hedge ratio may vary with time.

3.3 The risk-minimizing hedge ratio

The second category of hedge ratios to be studied is the risk minimizing hedge ratio. Under this technique, the correlation between the spot asset and the futures contract to be used for hedging is evaluated by performing an Ordinary Least Squares (OLS) regression of the return on the spot asset on the return of the futures contract (Ederington, 1979). Mathematically, it takes the following form:

$$\mathbf{r_{s,t} = \alpha + \beta\, r_{f,t} + \varepsilon_t} \qquad \mathbf{(3)}$$

Where $r_{s,t}$ is the return on the spot asset, α is a constant term, $r_{f,t}$ is the return on the futures contract, β is the static risk minimizing hedge ratio and ε_t is an error term.

This second approach solves the first problem encountered with the naive hedge since it calculates the correlation coefficient between the two instruments. However, it still assumes that the joint distribution of the spot and futures returns remains constant over time and as such produces a static hedge ratio.

3.4 The modified risk-minimizing hedge ratio

The third set of hedge ratios, the modified risk-minimizing hedge ratios, were created to correct for the presence of serial correlation in the residuals of equation (3). Indeed, a Durbin-Watson diagnostic test performed on the OLS regression showed significant negative serial correlation in ε_t for all companies under study. Therefore, the Hildreth-Lu procedure was applied in order to eliminate the serial correlation and provide a more efficient estimate of the hedge ratio β_t . Serial correlation in the residuals can be represented by the following:

$$r_{s,t} = \alpha + \beta\, r_{f,t} + \varepsilon_t \qquad (3)$$

where

$$\varepsilon_t = \rho\, \varepsilon_{t-1} + v_t \quad , \quad 0 \leq |\rho| \leq 1 \qquad (4)$$

In equation (3), ε_t is distributed as N $(0 , \sigma^2_\varepsilon)$ but is not independent of past errors. In equation (4), v_t is distributed as N $(0 , \sigma^2_v)$ and is independent of other errors. The Hildreth-Lu procedure is a searching method whose aim is to find the ρ value which yields the lowest sum-of-squared residuals in the following transformed equation:

$$r_{s,t} - \rho\, r_{s,t-1} = \beta_0\, (1-\rho) + \beta_t\, (r_{f,t} - \rho\, r_{f,t-1}) + v_t \qquad (5)$$

Therefore, the modified risk-minimizing hedge ratio is β_t in equation (5). Also, it should be noted that the assumption of constant joint distribution of spot and futures returns still holds thus yielding a static hedge ratio which is applied over the entire hedging period.

3.5 The time-varying hedge ratio under a GARCH (1,1) process

In order to solve for the fact that the variance of the error term in equation (3) may vary over time with past errors, researchers have developed a family of econometrics models called ARCH (Autoregressive Conditional Heteroskedastic). This process was introduced in Engle (1982) following the belief that the joint distribution of returns varies in time according to the magnitude of errors in the recent past, thereby forming periods of high volatility followed by periods of low volatility. Under the ARCH process, the conditional variance changes through time in relation with past errors while an unconditional variance remains constant. The ARCH (p) model can be expressed as follows:

$$r_{s,t} = \alpha + \beta\, r_{f,t} + \varepsilon_t \qquad (3)$$

From equation (3) we see that the returns on the spot asset are a function of the returns on the futures instrument in addition to a constant term and an error term.

$$\sigma^2_{\varepsilon,t} = \alpha_0 + \alpha_1\, \varepsilon^2_{t-1} + \ldots + \alpha_p\, \varepsilon^2_{t-p} \qquad (6)$$

Equation (6) defines the variance of the error term as $\sigma^2_{\varepsilon,t}$ and makes it dependent on the magnitude of volatility in recent periods. Therefore, the variance of ε_t contains two parts: an unconditional variance which is constant and a conditional variance related to the square of previous periods' residuals which are called ARCH terms. Equations (3) and (6) are solved by maximum likelihood estimation. It is believed that by allowing the variance of the error term to be a function of past errors, more efficient estimates of the β coefficients may be obtained. However, empirical studies have found that many periods of past errors had to be included in the conditional variance equation and that a fixed lag structure was necessary in order to prevent negative variance parameter estimates which would cause computational problems. Following these findings, Bollerslev (1986) made the ARCH framework more widely applicable by extending the ARCH model to accommodate a longer memory of past errors and a more flexible lag structure thereby instigating the GARCH (Generalized Autoregressive Conditional Heteroskedastic) family of models. Under a GARCH (p,q) model, the variance of the error term can be represented as follows:

$$\sigma^2_{\varepsilon,t} = \alpha_0 + \alpha_1\ \varepsilon^2_{t-1} + \dots + \alpha_p\, \varepsilon^2_{t-p} + \delta_1\, \sigma^2_{\varepsilon,t-1} + \dots + \delta_q\, \sigma^2_{\varepsilon,t-q} \qquad (7)$$

From equation (7) we denote that the variance of ε_t now has three components: an unconditional variance which remains constant, a conditional variance based on previous periods' volatilities (the ARCH terms) and a conditional variance related to previous periods' variances (the GARCH terms). Therefore, while the ARCH process imposed the conditional variance to be a linear function of past volatilities alone, the GARCH process, in addition, complements the equation with lagged conditional variances with geometrically declining weights. Furthermore, as with the ARCH models, the GARCH models are estimated with the maximum likelihood method.

Many different GARCH models have been created to best fit different data sets. However, the literature on Index futures (Park & Switzer, 1995; Brooks et al., 2002) seems to indicate that for this type of asset, the bivariate GARCH (1,1) is the model which provides the best fit and is the one that will be employed in this thesis because of the similarity between the two products. Under the bivariate GARCH (1,1) model, the variances and covariance of both assets are allowed to vary through time while the correlation ρ between the two instruments remains constant thereby yielding stochastic hedge ratios which should provide a better hedge to the underlying portfolio. It can be computed as follows:

$$r_{s,t} = \alpha_s + \varepsilon_{s,t} \quad \textbf{(8a)}$$

$$r_{f,t} = \alpha_f + \varepsilon_{f,t} \quad \textbf{(8b)}$$

$$\begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{bmatrix} Z_{t-1} \sim N(0, H_t) \quad \textbf{(8c)}$$

$$H_t = \begin{bmatrix} \sigma_{ss,t} & \sigma_{sf,t} \\ \sigma_{sf,t} & \sigma_{ff,t} \end{bmatrix} = \begin{bmatrix} \sigma_{s,t} & 0 \\ 0 & \sigma_{f,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sigma_{s,t} & 0 \\ 0 & \sigma_{f,t} \end{bmatrix} \quad \textbf{(8d)}$$

$$\sigma^2_{\varepsilon s,t} = \alpha_0 + \alpha_1 \ \varepsilon^2_{s,t-1} + \delta_1 \ \sigma^2_{\varepsilon s,t-1} \quad \textbf{(8e)}$$

$$\sigma^2_{\varepsilon f,t} = \alpha_0 + \alpha_1 \ \varepsilon^2_{f,t-1} + \delta_1 \ \sigma^2_{\varepsilon f,t-1} \quad \textbf{(8f)}$$

where ε_s and ε_f are the error terms for the spot and futures series respectively, $\sigma_{sf,t}$ is a conditional covariance and $\sigma^2_{s,t}$ is a conditional variance. The first two equations represent the conditional mean returns, equations (8c) and (8d) describe the conditional VCV (variance-covariance) matrix and finally, the hedge ratio is computed as $\sigma_{sf,t}$ / $\sigma^2_{f,t}$ from the last two equations. For this study, the GARCH computations were produced with the use of the RATS software version 5 from Estima. The program can be found in appendix 9.1 at the end of this thesis.

4. DATA

4.1 Description of the sample

The aim of this study is to assess the hedging effectiveness of different hedge ratios when hedging a spot position in a stock with its stock futures contract. The research will be conducted on the Universal Stock Futures traded on the Euronext/LIFFE exchange. These products were preferred over their American or Australian counterparts because they were a good compromise between the number of companies on which the contracts were available and the length of time these new products had been trading. Indeed, the Single-Stock Futures traded on exchanges in the United States were based on a large range of companies but they only started to trade in late 2002 and the Individual Share Futures in Sydney have been trading since 1994, but they are based on only a dozen companies. The initial sample contained each European company on which Universal Stock Futures contracts started to trade from the initial launch on January 29th 2001 until October 31st 2001. During this period, six contract launches were performed on the following dates: January 29th 2001, March 19th 2001, April 3rd 2001, April 30th 2001, May 14th 2001 and October 31st 2001. This time span was selected in order to ensure that a two-year period of data would be available for all companies prior to the beginning of the analysis which started in November 2003. It should be noted that Universal Stock Futures also began to trade on American companies but they were not included in the study because the effect of their impending trading on American Derivatives Exchanges could have introduced an element of competition among market makers and yielded atypical results as well as a decrease in the volume of contracts traded. A total of 76 companies were part of the initial sample. From this initial sample, seven companies had to be eliminated because various data could not be found on the relevant databases. Also, four companies had contracts calling for the physical delivery of shares and, to maintain a homogeneity of treatment among contracts, they were not retained for the analysis. Therefore, a total of 65 companies were included in this research.

4.2 Description of the data

For each company, daily adjusted closing prices and adjusted dividend amounts were collected from the database Datastream. Daily futures settlement prices were retrieved via a subscription to the Euronext/LIFFE website. The data were collected for a period of two years following the launch of each contract. The futures settlement prices were adjusted for stock splits, the dividend amounts were verified through each company's website and the futures settlement prices were drawn from the contract with the nearest maturity without being the current month's contract in order to avoid the expiration effect and the atypical trading occasionally found in the expiry month. The spot daily returns and the futures daily returns were calculated with the following formulas:

$$\textbf{Spot daily return} = \ln\left(\left(price_t + div_t / price_{t-1}\right)\right) \qquad \textbf{(9)}$$

$$\textbf{Futures daily return} = \ln\left(price_t / price_{t-1}\right) \qquad \textbf{(10)}$$

Daily returns were preferred over weekly or monthly returns because they are widely used in the literature (Park & Switzer 1996, Lee & Tong 1998, Dennis & Sim 1999, Lien

& Tse 2001, Choudhry 2003) and since the estimation period was only one year in length, it allowed a greater amount of data to be utilized.

4.3 Descriptive statistics

Tables I (a-h) present the descriptive statistics for the return data of the spot and futures series for each company subdivided by country of origin. The mean statistic represents the average daily return for the two-year period that the collected data covers. This statistic can be represented with the following formula:

$$\bar{x} = (1/N) \sum_{i=1}^{N} x_i \qquad (11)$$

Where N is the total number of observations and x_i are the daily return data. Tables I (a-h) show that over the two years covered by the research, most companies exhibited a negative average daily return and the other firms only showed a slight positive average daily return. This implies that the European stock market experienced a downturn during the two years covered by the analysis. Also, the futures average daily returns are very close to the spot average daily returns but always offer a worse performance than its spot counterpart. Finally, Swiss companies covered by the study had the best group performance (-.0001) while the Netherlands showed the most negative returns (-.0018).

The Variance statistic is a measure of the spread or dispersion of the daily returns around their mean and is provided for the spot and the futures series. It can be represented by the following formula:

$$S^2 = [\, 1 / (N-1) \,] \sum_{i=1}^{N} (x_i - \bar{x})^2 \qquad (12)$$

Where N is the total number of observations, x_i are the daily return data and $\bar{x}$ is the average daily return over the two-year period. Tables I (a-h) show that the variance of daily returns has approximately the same magnitude for the spot and the futures series. Italy and Switzerland had companies with the lowest variance of returns (.0005) while the Dutch firms as a group had more volatile returns (.0016). These statistics seem to support the theory that the higher the risk, the bigger the gain or loss. Indeed, Switzerland and Italy have more stable returns and the smallest loss in this downward market while the Netherlands was the riskiest country and showed the biggest loss. On an individual basis, companies such as: Alcatel SA, France Telecom SA, Vivendi Universal SA, Koninklijke Ahold NV and T. LM Ericsson also seem to support this concept by demonstrating a higher variance and a higher negative mean.

The skewness statistic is a measure of the shape of the return distribution. A value equal or close to zero would describe a symmetric data distribution around the mean. A positive measure would imply that the upper tail is thicker than the lower tail and vice versa for a negative value. The statistic can be calculated as follows:

$$Sk = (N^2 / ((N-1)(N-2))) * (m_3 / s^3) \qquad (13)$$

and

$$m_k = 1/N \sum_{i=1}^{N} (x_i - \bar{x})^k \qquad (14)$$

In the formulas above, N is the total number of observations, x_i are the daily return data, $\bar{x}$ is the average daily return over the two-year period and s is the standard deviation of the daily returns over the two-year period. Tables I (a-h) denote that the average spot and futures distributions have the same shape being either both skewed positively or negatively. Only nine companies do not exhibit this characteristic. Also, the magnitude of the skewness can be quite different between the spot and the futures distribution of a company ranging from .0005 to 1.5701. Only one company Koninklijke Ahold NV of the Netherlands stands out with a measure of –9.5643 and –9.8402 for the spot and futures series respectively. A close inspection of its data series showed a daily negative return of around 63% on February 24th 2003. However, inquiries conducted on the LIFFE/Euronext as well as on the company's own websites did not provide any mention of a stock split, dividend announcement or any other corporate event which might have caused such a decrease in the share value around that date. Therefore, the data remained unchanged for the analysis.

The excess kurtosis statistic is a measure of the thickness of the tails of the distribution. A value greater than zero would imply thicker tails than the normal distribution and hence a peaked distribution concentrated around the mean. A negative value would imply a flatter distribution than the normal shape and hence thinner tails. The statistic can be mathematically represented by the following formula:

$$\textbf{Excess Ku} = \left(N^2 / ((N-1)(N-2)(N-3)) \right) * \left(\left(((N+1)\, m_4) - (3(N-1)\, m_2^2) \right) / s^4 \right) \qquad (15)$$

and

$$m_k = 1/N \sum_{i=1}^{N} (x_i - \bar{x})^k \qquad (14)$$

In the above formulas, N is the total number of observations, x_i are the daily return data, $\bar{x}$ is the average daily return over the two-year period and s is the standard deviation of the daily returns over the two-year period. Tables I (a-h) demonstrate that a peaked distribution characterizes both the spot and the futures series and the magnitude of this departure from the normal distribution can vary greatly between the spot and futures series of a company. Indeed, the difference between the excess kurtosis of the spot and futures distributions ranges from .0007 to 18.25. Also, most companies have similar measures for their spot and futures series except HSBC Holdings plc, Bayer AG, Alcatel SA and Koninklijke Ahold NV. However, a close inspection of the data series and company events showed no reason to disregard part of the data.

Finally, the Jarque-Bera measure is a statistic which computes a value for the normality of the distribution based on the skewness and the kurtosis measures combined. This test follows a chi-square distribution with 2 degrees of freedom and can be represented with the following formula:

$$\mathbf{JB = N\,(((Ku)^2 / 24) + ((Sk)^2 / 6))} \qquad \mathbf{(16)}$$

Where N is the total number of observations, Ku is the kurtosis measure and Sk is the skewness value. With a chi-square critical value of 5.99 at the 5% level , tables I (a-h) show that the spot and futures series of returns do not exhibit a normal distribution. With an average Jarque-Bera value of 9658.39 for the spot series and 10165.30 for the futures series we can safely state that most distributions depart strongly from normality mainly due to the high excess kurtosis value affecting most series.

5. EMPIRICAL RESULTS

5.1 Description of the analysis

This study is based on data collected over the two-year period following the launch of each contract. Prices and dividends for a period of 507 to 513 days were retrieved from the relevant databases. The first year of data, consisting of between 254 and 258 days is used to calculate the relevant hedge ratios and the second year of data is employed to evaluate the performance of the hedged portfolios. Therefore, the analysis is conducted on an ex-ante basis in order to better reflect portfolio managers' decision making process and in turn allow for more valid conclusions to be drawn from the research.

The hedged portfolio returns can be represented by the following equation:

$$\mathbf{P_t = s_t - \beta_t f_t} \qquad \mathbf{(17)}$$

Where P_t is the return on the portfolio, s_t is the change in the spot asset's price adjusted for dividends when applicable, β_t is the hedge ratio and f_t is the change in the futures price.

In this study, five different portfolios are analyzed. The first one is the unhedged portfolio where no hedging activity takes place and the daily returns of the spot asset are simply averaged over the second year of data. Consequently, this portfolio should underperform all other hedged portfolios in the hedging effectiveness analysis. The second portfolio to be studied is the naive 1:1 hedge portfolio where the β value in equation (17) is set equal to one. The simplicity of this strategy should yield worse results than the other hedged portfolios which employ more sophisticated techniques. The third portfolio under study is the risk-minimizing hedge portfolio with a β value calculated via an OLS regression on the first year of data. The constant single β estimate is then applied over the second year of data thereby creating a static hedge strategy. The fourth portfolio hedge ratio, the modified risk-minimizing hedge, was created in an attempt to improve on the basic risk-minimizing hedge ratio by eliminating problems detected with the diagnostic tests performed on the OLS regression. First, observations set more than three standard deviations from the mean were discarded from the computations in order to avoid large price fluctuations from influencing a long-term hedge ratio. Also, the Durbin-Watson measure showed the presence of negative serial correlation for all companies. Therefore, the Hildreth-Lu procedure was applied to the regression to eliminate the correlation and hopefully improve the performance of the original risk-minimizing hedge ratio. Finally, the fifth portfolio is the time-varying GARCH (1,1) hedge portfolio with a ratio changing on a daily basis and calculated over the 250 days immediately preceding the hedge day. Therefore, day after day, the hedge ratio is computed via a 250-day moving window of data which adds data from the next day and discards the data from the first day of the preceding window thereby using only the 250 most recent observations in the calculations.

Tables II (a-h) show the different hedge ratios computed for each company. The risk-minimizing hedge ratio ranges from .7844 to 1.0337, the modified risk-minimizing hedge ratio spans values from .8465 to 1.0416 and is closer to unity than the basic risk-minimizing hedge ratio. Finally, the time-varying GARCH hedge ratios which are allowed to change on a daily basis, vary considerably ranging from –.1289 to 2.7093. However, its average value is similar to the modified risk-minimizing hedge ratio for most companies.

5.2 The R-squared measure

The R^2 measure pertains to the two risk-minimizing hedge ratios and defines the percentage of the variation in the dependent variable (spot returns) which is explained by the regression equation and as such, the independent variable (futures returns). Therefore, the higher the R-squared value, the better the fit of the regression line and the more accurate the hedge ratio estimate should be. Tables III (a-h) show the statistics of the OLS regressions. The R^2 values for the basic OLS regressions range from .62 to .96 while the R^2 measure for the modified OLS regressions are between .75 and .98. Therefore, one can conclude that the modified OLS regressions provide a better fit to the data than the basic OLS regressions since the range of values is closer to unity and that a closer inspection of the statistic shows that for each company, the modified OLS regression yielded a higher R^2 than its basic counterpart.

5.3 The Durbin-Watson Test

The Durbin-Watson measure is also applicable to the OLS regressions and is a test for first-order serial correlation in the residuals. Since no lagged variables are present in the regressions, this measure can provide a good assessment for a lack of randomness in the error term. A value close to 2.0 would indicate no serial correlation, higher values would denote negative serial correlation and lower values would indicate positive serial correlation. More precisely, for this study with $N \geq 100$ and only one predictor variable in the regression, the Durbin-Watson table at $\alpha = .05$ indicates that values above 2.35 denote negative serial correlation while values below 1.65 define positive serial correlation. Values between 1.69 and 2.31 indicate no serial correlation and indeterminate results can be concluded for values from 1.65 to 1.69 and from 2.31 to 2.35. Tables III (a-h) show the presence of negative serial correlation for all companies with Durbin-Watson values ranging from 2.5290 to 3.1884 when the basic OLS regression was applied to the data. In order to correct for this shortcoming and potentially enhance the ability of the regression equation to yield a more efficient hedge ratio, the Hildreth-Lu procedure was implemented in the modified OLS regression. The Hildreth-Lu process selects the correlation value of the residuals which produces the regression equation with the lowest sum of squared residuals. Tables III (a-h) demonstrate that the Durbin-Watson measure denotes no correlation in the modified OLS regression once the Hildreth-Lu correction has been applied. Indeed, the Durbin-Watson measure lies between 1.9163 and 2.3044 which is within the allowed boundaries.

5.4 The augmented Dickey-Fuller Test

The Dickey-Fuller test is a measure of whether a data series shows a unit root or random walk. When a variable exhibits a random walk, shocks to its long term trend do not dissipate over time but rather impact the data series permanently. Therefore, a hedge ratio based on past data would not provide an effective hedging technique since future shocks to the time series trend would change the nature of the stochastic process and this impact would not revert back to a long-term stationary direction. Also, it should be noted that the Dickey-Fuller test assumes that no serial correlation is present in the regression's residuals ε_t. Because the Durbin-Watson measure demonstrated the presence of negative serial correlation in the regression's residuals, the augmented Dickey-Fuller test was used with the optimal number of lags calculated via a program included in the RATS software. Table IV (a-h) shows that the spot and futures series as well as the residuals series from an OLS regression of the spot returns on the futures returns do not exhibit random walk or unit roots. Indeed, with critical values of –3.458, -2.874 and –2.573 at the 1%, 5% and 10% levels respectively, augmented Dickey-Fuller values ranging between –18.12 and –3.73 for the spot series, –18.98 and –3.88 for the futures series and –17.22 and –2.77 for the residuals series, one can safely conclude that all series are stationary in nature and that historical data can be used to compute efficient hedge ratios. The only company which does not show stationarity of the residuals series at the 1% level is Alcatel S.A. with an augmented Dickey-Fuller value of –2.77 which is significant at the 10% level.

5.5 The Ljung-Box autocorrelation test

The Ljung-Box Q statistic is a measure of higher-order autocorrelation present in a regression's residuals. The OLS regression process assumes that the error terms are distributed normally and independently from one another. If this assumption about the residuals is valid, one would expect them to exhibit white noise and be uncorrelated with each other. The Q statistic is used to verify the correlation among error terms at different lags or leads. If the error terms are found to be correlated, one could conclude that an

OLS regression would be misspecified for the set of data. The Q statistic follows a χ^2 distribution with the degrees of freedom equal to the number of leads or lags. Critical values for 1 lag are 6.63, 3.84 and 2.71 at the 1%, 5% and 10% levels respectively. For the 5 lags scenario, critical measures are 15.09, 11.07 and 9.24 at the 1%, 5% and 10% levels respectively. Finally, the χ^2 values with 24 degrees of freedom are 42.98, 36.42 and 33.20 at the 1%, 5% and 10% levels respectively. Tables IV (a-h) show the Q statistics for 1, 5 and 24 lags. With values ranging from 18.45 to 89.84 for 1 lag, 27.91 to 133.68 for 5 lags and 42.07 to 185.87 for 24 lags, all companies exhibit autocorrelation of the residuals for the three lags studied at the 1% level except San Paolo IMI SpA with a Q statistic significant only at the 5% level. Therefore, one can conclude that an OLS regression estimation is misspecified and that the GARCH process should yield more reliable estimates of the hedge ratio.

6. HEDGING EFFECTIVENESS

6.1 Comparison of portfolio variances

The hedging effectiveness of each hedge ratio will first be analyzed through the variance of the hedged portfolios. This procedure can be represented by the following:

$$\sigma^2_{p,t} \; (P_t = s_t - \beta_t f_t) \qquad \textbf{(18)}$$

where the lowest $\sigma^2_{p,t}$ value would indicate the best hedging effectiveness. Tables V (a-h) show the portfolio variance for each company under each hedging technique. The numbers in bold indicate the lowest variance and therefore the best hedging strategy for each company. The values between parentheses show the percentage increase in portfolio variance relative to the lowest variance portfolio. The findings seem to suggest that the time-varying GARCH hedge ratio is a better hedging strategy when aiming to decrease the volatility of returns. This technique outperformed all others for 49 of the 65 companies studied. The risk-minimizing hedge ratio follows with outperformance in 6 firms. The naive 1:1 and the modified risk-minimizing hedge ratios did better than all others for 5 firms each. The unhedged portfolio always underperformed the hedging strategies as was expected prior to the analysis. These results indicate that a dynamic hedge ratio reassessed on a daily basis provides a better hedge against market fluctuations. Furthermore, the analysis demonstrates that hedging a stock spot position with its futures contract reduces the variance of portfolio returns by 76.45% to 97.36% relative to an unhedged portfolio. Also, the constant hedge ratios namely the naive 1:1

hedge, the risk-minimizing hedge and the modified risk-minimizing hedge seem to provide about the same variance reduction for a majority of the firms under study and when the time-varying hedging technique underperforms its constant counterparts, it is by no more than 25%. The individual tables demonstrate that the time-varying hedging strategy offers the following reduction in portfolio variance compared to the constant hedge ratios: 10-30% for the United Kingdom, 25-40% for the Netherlands, Switzerland, Sweden and Spain, 20-60% for Germany and Italy and finally, 20-90% for France. On the other hand, among the Swedish companies analyzed, the risk-minimizing hedge ratio increased portfolio variance by twice the amount of the other constant ratios for half the companies under study. Furthermore, the four hedging techniques offer about the same minimal portfolio variance reduction for the following companies: Barclays plc, BP plc, Diageo plc, HBOS, and Koninklijke Philips Electronics NV. Finally, the modified risk-minimizing ratio provided a perfect hedge for Tesco plc during the period studied.

6.2 Significance of differences among portfolio variances

In order to investigate whether the reductions in portfolio variances are significant between the various hedging techniques, an F-Test for equality of factor level means is conducted on the portfolio variances obtained in the previous analysis. An analysis of Variance table (ANOVA) was first achieved in order to generate the necessary data to conduct the F-Test which can be described as follows:

$$H_0 = \sigma^2_1 = \sigma^2_2 = \sigma^2_3 = \sigma^2_4 \quad \text{(19a)}$$

$$H_a = \text{not all } \sigma^2_i \text{ are equal} \quad \text{(19b)}$$

$$F^* = MSTR/MSE \quad \text{(20)}$$

$$\text{If } F^* \leq F\,(1-\alpha;\, r-1,\, n_T - r)\text{, conclude } H_0 \quad \text{(21a)}$$

$$\text{If } F^* > F\,(1-\alpha;\, r-1,\, n_T - r)\text{, conclude } H_a \quad \text{(21b)}$$

Where r is the number of factors under study and n_T is the total number of observations. Therefore, the lower the p-value, the more likely the conclusion toward H_a that not all portfolio variances are equal.

Table VI (a-i) shows the results of the analysis over the whole data set and for each country. The upper section of each table presents the F statistic with its p-value between parentheses when comparing the different hedge ratios with one another. The lower portion of the table shows the same results over all ratios. It should be noted that due to the relatively small number of observations in tables (b-i), conclusions reached through these analyses might not be robust. Table VI (a) indicates that there is a significant difference between portfolio variances stemming from the various hedge ratios. Also, there is a significant difference between the variances of unhedged portfolios and the variances of hedged portfolios irrespective of the hedging technique employed. Furthermore, the portfolio variances among the diverse constant hedge ratios do not appear to be significantly different from one another. Finally, the portfolio variances pertaining to the time-varying GARCH ratios seem to differ from the constant hedging strategies at the 10% level of significance.

6.3 Mean-Variance utility analysis

The previous analyses suggest that the time-varying GARCH hedge ratio is the best strategy to reduce the volatility of portfolio returns. However, the study did not investigate the mean-variance trade-off, in other words whether the lower variance from the hedged portfolio is sufficient to compensate for the decreased mean return that results from a hedging strategy. In order to investigate this question, the following mean-variance utility function was used:

$$\mathbf{E(U) = E(R_p) - \delta\, \sigma^2_p \quad (22)}$$

Where $E(R_p)$is the expected return on the portfolio, δ is the risk aversion parameter and σ^2_p is the variance of the portfolio. The risk aversion parameter can be estimated at 4 (Kroner & Sultan, 1993)[5] and the following equation is estimated for all companies:

$$\mathbf{U = (r_s - \beta\, r_f) - 4\, (\sigma^2_p (r_s - \beta\, r_f)) \quad (23)}$$

The return and the variance of the portfolio is estimated over the second year of data. The naive 1:1, risk-minimizing and modified risk-minimizing hedge ratios remain constant over the analysis. The GARCH hedge ratios are calculated on a daily basis but

[5] Based on Chou (1988) estimate of 4.5, Poterba & Summers (1986) estimate of 3.5 and Grossman & Shiller (1981) estimate of 4.

applied on a weekly basis as the average of the five preceding days ratios. Table VII (a-h) shows the utility amounts by company for each hedging strategy. The time-varying GARCH hedge is still the best technique with outperformance in 26 of the 65 companies followed closely by the naive 1:1 hedge which surpassed other strategies for 21 companies. The risk-minimizing and the modified risk-minimizing hedges had the best performance for 10 and 8 firms respectively. The transaction costs figure represents the commission percentage of the total value of the futures contracts which would equate the time-varying hedge and the next best strategy taking into account the fact that the constant hedge portfolios are rolled over on a monthly basis while the GARCH hedge portfolios are rebalanced on a weekly basis. This computation can be represented by the following:

$$\textbf{Utility of next best hedge} - \mathbf{12\ c} = \textbf{Utility of the GARCH hedge} - \mathbf{52\ c} \qquad \mathbf{(24)}$$

Where c is the commission costs incurred when rebalancing the portfolio. Results show that transaction costs varying between .0000175 and .0006975 would equate both techniques. Therefore, if the transactions can be executed at a lower cost, the time-varying GARCH strategy should be preferred.

7. CONCLUSION

This research aimed to examine the efficiency of four different hedge ratios namely the naive 1:1 hedge ratio, the risk-minimizing hedge ratio, the modified risk-minimizing hedge ratio and the time-varying GARCH (1,1) daily hedge ratio at hedging a stock spot position with its stock futures contract. To conduct the study, the Universal Stock Futures trading in London were used as well as their spot counterparts. The hedging effectiveness was first evaluated through the variance of portfolio returns where the lowest variance would indicate the best hedging strategy. Results show that the time-varying GARCH (1,1) hedge ratios outperformed other techniques for 75% of the companies under investigation. The risk-minimizing hedge ratio provided the best performance for 9% of the firms, the naive 1:1 and the modified risk-minimizing hedge ratios were the better hedging strategy for 8% each of the companies analyzed. Results also indicate that the hedging activity reduced portfolio variance by 76.45% to 97.36% and when the time-varying GARCH strategy underperformed the constant hedge ratios, it was by no more than 25%. Also, differences among portfolio variances were examined and the analysis showed that there was a difference between the portfolio variances stemming from the various hedging techniques. Furthermore, the variance of portfolios under the time-varying GARCH hedge were found to be significantly different from the constant hedges at the 10% level. However, no significant difference was found among portfolio variances coming from the constant hedge strategies. Finally, the mean-variance utility was investigated in order to determine whether the lower variance from the hedged portfolios was sufficient to compensate for the decreased mean return that results from a hedging strategy. Results showed that the time-varying GARCH hedging strategy still outperformed other techniques for 40% of the companies studied but that relatively low transaction costs would have to be incurred.

Previous research has shown that the time-varying GARCH hedging technique should outperform constant hedge ratios since it better tracks the variance in the error term and hence should consistently provide the best hedge. However, this thesis noted instances where a constant hedge ratio proved more effective at hedging a spot position. This could be due to the relatively short period of time under study. A longer data period might give a more accurate evaluation of the variance in the residuals behavior. Furthermore, even though futures settlement prices were used in the analysis, the thin trading that some futures contracts experienced did not allow for a market assessment of the contract's prices. Finally, only the GARCH (1,1) model was used in estimating the daily hedge ratios. Another model in the GARCH family might have yielded better results for some of the firms.

Since single stock futures contracts are relatively new to the market, research in this area is fairly limited. Once the product will have established a suitable trading history, future study could investigate which GARCH (p,q) model provides the best hedging technique. Also, researchers could examine the hedging effectiveness of single stock futures compared to options strategies that should yield the same outcome. Finally, the question of the impact of the Universal Stock Futures on the underlying spot market's volatility could also be explored.

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TABLE I - a

Descriptive statistics - United Kingdom

United Kingdom										
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Abbey National plc	-0.0010	-0.0012	0.0007	0.0007	0.0677	0.1852	1.3001	1.6504	36.0234	60.3220
AstraZeneca plc	-0.0008	-0.0009	0.0005	0.0005	0.0907	0.2112	4.6362	5.1965	458.3470	578.7522
Aviva plc	-0.0009	-0.0011	0.0010	0.0010	0.1335	0.3013	2.1733	2.3881	101.0850	127.8988
Barclays plc	-0.0004	-0.0006	0.0007	0.0008	0.0775	0.1030	1.0692	1.4316	24.7049	44.2763
BP plc	-0.0007	-0.0009	0.0005	0.0005	-0.7252	-0.8863	3.4800	4.1242	301.4606	427.3745
Diageo plc	0.0002	0.0000	0.0003	0.0003	0.0303	0.0162	2.8242	2.4310	167.9071	124.3721
GlaxoSmithKline plc	-0.0009	-0.0010	0.0004	0.0004	0.1170	0.1258	2.5928	3.1403	143.7326	210.4886
HBOS	-0.0001	-0.0002	0.0006	0.0006	0.3756	0.3576	1.7819	1.8493	78.6897	82.7184
HSBC Holdings plc	-0.0009	-0.0010	0.0004	0.0004	-0.5499	-0.1408	6.0855	2.6125	811.0696	146.4269
Legal&General Grp	-0.0004	-0.0008	0.0008	0.0008	0.0856	-0.1309	1.1269	1.5756	27.3373	53.6788
Lloyds TSB Grp plc	-0.0011	-0.0014	0.0006	0.0006	0.0643	0.1889	1.2605	1.4326	33.9788	46.4605
Royal Bank Scotland	0.0001	-0.0001	0.0007	0.0006	-0.0668	0.0417	1.4961	1.6692	47.7579	59.1237
Sainsbury (J) plc	-0.0004	-0.0005	0.0004	0.0004	0.0423	-0.0250	2.0033	2.3786	84.5966	119.1015
Shell T&T Co. plc	-0.0005	-0.0007	0.0005	0.0005	-0.5893	-0.6971	2.9891	4.5178	218.5218	473.1689
Tesco plc	0.0000	0.0000	0.0004	0.0004	0.0427	0.2605	2.4270	3.5938	124.0927	277.4637
Unilever plc	0.0001	0.0000	0.0003	0.0003	-0.5891	-0.5824	5.9040	6.6594	762.6671	961.6890
Vodafone Group plc	-0.0016	-0.0016	0.0011	0.0010	0.3015	0.2808	0.1958	0.2568	8.5239	8.0858
Average	-0.0005	-0.0007	0.0006	0.0006	-0.0642	-0.0230	2.5498	2.7593	201.7939	223.6118

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - b

Descriptive statistics - Germany

	Germany									
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Allianz AG	-0.0036	-0.0036	0.0010	0.0011	-0.0218	-0.2498	1.4135	1.7892	42.3307	73.0459
BASF AG	0.0002	0.0001	0.0005	0.0005	0.2928	0.2277	1.8132	1.6614	76.5483	62.5673
Bayer AG	-0.0008	-0.0010	0.0010	0.0009	1.9493	0.3792	24.0091	5.7591	12,473.6121	711.3965
Bayerische H&V AG	-0.0032	-0.0032	0.0014	0.0014	-0.0027	-0.4074	1.5661	2.5323	51.9175	149.7856
DaimlerChrysler AG	-0.0013	-0.0014	0.0007	0.0008	-0.0277	0.0298	0.4521	0.5942	4.3905	7.5481
Deutsche Bank AG	-0.0018	-0.0019	0.0007	0.0008	-0.1934	-0.1750	1.7436	2.4839	67.6480	133.4469
Deutsche Telekom	-0.0020	-0.0022	0.0011	0.0012	0.2188	0.1930	0.9686	0.6470	23.9576	12.0375
E.ON AG	-0.0003	-0.0005	0.0005	0.0005	0.2774	0.4584	1.3445	1.9250	44.7746	96.2301
MRG AG	-0.0033	-0.0033	0.0011	0.0013	-0.3828	-0.2024	3.4994	3.8780	271.6017	321.7821
SAP AG	0.0002	0.0001	0.0012	0.0012	0.8220	0.6927	5.2524	4.3626	637.3578	440.8541
Siemens AG	-0.0019	-0.0020	0.0010	0.0011	0.3658	0.3271	0.7002	0.7853	21.7480	22.1569
Volkswagen AG	-0.0010	-0.0012	0.0007	0.0008	-0.0941	-0.2175	1.1107	1.3952	26.8611	45.2078
Average	-0.0016	-0.0017	0.0009	0.0010	0.2670	0.0880	3.6561	2.3178	1,145.2290	173.0049

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - c

Descriptive statistics - France

France

Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Alcatel SA	-0.0044	-0.0045	0.0028	0.0035	0.4917	0.8371	4.4454	12.5919	439.6254	3,422.1619
Aventis SA	-0.0011	-0.0012	0.0006	0.0007	-0.0490	-0.0682	1.1177	2.3994	26.5406	121.7713
Axa SA	-0.0017	-0.0018	0.0015	0.0016	0.1897	0.0651	1.3890	1.6781	43.8807	59.9618
BNP Paribas SA	-0.0002	-0.0003	0.0007	0.0007	-0.0321	-0.2452	3.0277	3.9962	194.1202	343.1160
Carrefour SA	-0.0010	-0.0011	0.0006	0.0006	0.0412	-0.1068	1.5998	1.5991	54.3158	55.0917
France Telecom SA	-0.0025	-0.0027	0.0022	0.0021	0.3873	0.3986	1.5627	1.6953	64.5195	74.4306
Sanofi-Synthelabo	-0.0006	-0.0006	0.0006	0.0006	0.1378	0.1155	1.4941	1.2971	48.5684	36.5266
Suez SA	-0.0017	-0.0018	0.0014	0.0012	0.0756	-0.1007	2.3086	1.9933	112.6268	84.4591
Total SA	-0.0004	-0.0005	0.0004	0.0004	-0.5749	-0.5036	3.3746	3.9128	269.5557	346.2178
Vivendi Universal SA	-0.0033	-0.0034	0.0024	0.0022	-1.0126	-1.1668	8.2264	8.8217	1,519.2524	1,762.4824
Average	-0.0017	-0.0018	0.0013	0.0014	-0.0345	-0.0775	2.8546	3.9985	277.3005	630.6219

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - d

Descriptive statistics - Italy

Italy										
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Ass. Generali SpA	-0.0011	-0.0011	0.0005	0.0005	-0.2978	-0.1509	1.4481	1.4787	51.8960	48.2113
Enel SpA	-0.0003	-0.0006	0.0004	0.0004	-0.5029	-0.4355	3.1863	3.2151	236.3013	234.8540
Eni SpA	0.0001	0.0000	0.0004	0.0004	-0.4594	-0.5573	1.1936	1.7183	48.1192	88.9729
MediaSet SpA	0.0005	0.0004	0.0005	0.0006	0.3057	0.3242	0.8731	0.6539	23.9034	17.8417
San Paolo IMI SpA	-0.0002	-0.0004	0.0007	0.0007	0.2601	0.0991	1.0078	0.8381	27.0641	15.6058
Telecom Italia Mobile	-0.0008	-0.0011	0.0006	0.0006	0.1891	-0.1640	1.8567	1.4744	76.0001	48.2917
Telecom Italia SpA	-0.0009	-0.0011	0.0005	0.0005	-0.3846	-0.3841	3.1582	2.6362	223.6420	159.5847
UniCredito Italiano	-0.0004	-0.0005	0.0005	0.0005	0.2539	0.3144	3.2129	3.3033	223.9578	239.3319
Average	-0.0004	-0.0006	0.0005	0.0005	-0.0795	-0.1193	1.9921	1.9148	113.8605	106.5867

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - e

Descriptive statistics - Netherlands

Netherlands										
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
ABN AMRO Hold.NV	-0.0005	-0.0007	0.0010	0.0010	0.0576	0.0449	2.1919	2.5477	101.9731	137.5571
Aegon NV	-0.0025	-0.0027	0.0017	0.0016	-0.0589	-0.0879	2.4683	2.5289	128.9945	135.7568
ING Groep NV	-0.0021	-0.0023	0.0012	0.0012	-0.1333	-0.1399	2.7833	2.7901	165.7986	166.7589
Koninklijke Ahold NV	-0.0035	-0.0035	0.0034	0.0034	-9.5643	-9.8402	167.9081	173.4030	604,499.8574	644,650.5493
K.Philips Electr. NV	-0.0011	-0.0012	0.0016	0.0016	0.0244	0.1104	0.3445	0.2769	2.5630	2.6550
Royal Dutch Petro.	-0.0010	-0.0011	0.0005	0.0005	-0.7051	-0.7268	4.1547	4.3547	408.2568	446.9886
Average	-0.0018	-0.0019	0.0016	0.0015	-1.7299	-1.7732	29.9751	30.9836	100,884.5739	107,590.0443

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - f

Descriptive statistics - Switzerland

Switzerland										
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Crédit Suisse Group	-0.0003	-0.0005	0.0011	0.0012	-0.1760	-0.0140	2.2913	2.2825	113.0794	2.2825
Nestle SA	-0.0002	-0.0003	0.0003	0.0003	0.2058	0.1006	3.5180	2.4173	263.9839	123.8078
Novartis	-0.0003	-0.0004	0.0003	0.0003	0.2788	0.4621	2.1493	2.2461	103.7419	124.1218
Roche Holdings AG	0.0000	-0.0001	0.0004	0.0004	-0.0384	0.1848	1.5729	1.5643	52.1843	54.3622
UBS AG	0.0003	0.0002	0.0005	0.0005	0.2790	0.0409	2.3937	3.6542	127.1192	281.1193
Average	-0.0001	-0.0002	0.0005	0.0005	0.1098	0.1549	2.3851	2.4329	132.0217	117.1387

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - g

Descriptive statistics - Sweden

Sweden										
Company	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Hennes&Mauritz AB	-0.0002	-0.0002	0.0005	0.0006	0.1713	-0.0347	4.2275	6.4720	378.5204	881.4740
Nordea AB	0.0002	0.0001	0.0007	0.0007	0.0595	0.1114	2.8816	3.0585	175.0251	197.8737
S. Handelsbanken	0.0002	0.0001	0.0003	0.0003	0.0889	0.1950	2.2530	2.2652	107.4745	111.1712
T. LM Ericsson	-0.0018	-0.0018	0.0027	0.0028	-0.0264	-0.1234	3.0971	3.3807	201.8854	241.7733
Average	-0.0004	-0.0005	0.0011	0.0011	0.0733	0.0371	3.1148	3.7941	215.7264	358.0730

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE I - h

Descriptive statistics - Spain

Company	Spain									
	Mean		Variance		Skewness		Kurtosis		Jarque-Bera	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
BBVA SA	-0.0012	-0.0013	0.0008	0.0007	0.3485	0.3037	0.8467	0.5217	25.4534	13.5693
Santander Ctrl Hisp.	-0.0012	-0.0013	0.0008	0.0007	0.1263	0.2770	1.1526	1.0561	29.5278	30.1658
Telefonica SA	-0.0015	-0.0016	0.0007	0.0007	0.3548	0.4820	1.4122	2.0152	52.9730	105.8291
Average	-0.0013	-0.0014	0.0008	0.0007	0.2765	0.3542	1.1371	1.1977	35.9847	49.8547

The descriptive statistics were calculated with daily returns computed through the following formulas: Spot daily return = ln ((price t+div. t / price t-1) and Futures daily return = ln (price t / price t-1). A skewness value close to zero would indicate a symmetric distribution, an excess kurtosis value close to zero would indicate normal distribution tails and the Jarque-Bera measure has a chi-square critical value of 5.99 at the 5% level of significance.

TABLE II - a

Hedge ratios - United Kingdom

United Kingdom					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
Abbey National plc	0.9269	0.9636	0.5691	1.0790	0.9775
AstraZeneca plc	0.9819	0.9877	0.2983	1.3688	0.9722
Aviva plc	0.9536	0.9250	0.8158	1.0378	0.9354
Barclays plc	0.8832	0.9883	0.6813	1.3605	0.9633
BP plc	0.9853	0.9767	0.8865	1.0858	0.9732
Diageo plc	0.9729	0.9852	0.8101	1.1390	0.9809
GlaxoSmithKline plc	1.0337	1.0416	0.7159	1.2156	0.9952
HBOS	0.9737	0.9824	0.8344	1.2129	0.9621
HSBC Holdings plc	1.0219	0.9708	0.7181	1.0749	0.9404
Legal & General Group plc	0.8510	0.9500	0.7472	1.0903	0.9755
Lloyds TSB Group plc	0.9444	0.9577	0.5690	1.3902	0.9722
Royal Bank of Scotland Group plc	0.9825	0.9855	0.5492	1.3182	0.9945
Sainsbury (J) plc	1.0023	0.9943	0.8513	1.4110	0.9927
Shell T&T Co. plc	0.8641	0.9781	0.8553	1.2697	0.9900
Tesco plc	0.9692	0.9736	0.7752	1.2418	0.9983
Unilever plc	0.9484	0.9429	0.7561	1.0983	0.9799
Vodafone Group plc	0.9914	1.0076	0.9253	1.2497	0.9924
Average	0.9580	0.9771	0.7269	1.2143	0.9762

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon\, t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - b

Hedge ratios - Germany

Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
	Germany		Minimum	Maximum	Average
Allianz AG	0.9247	0.9290	-0.0778	1.3840	0.9243
BASF AG	0.8799	0.8963	0.5895	1.0479	0.8917
Bayer AG	0.8324	0.8940	-0.1289	2.7093	0.8927
Bayerische H&V AG	0.8012	0.9145	0.3851	1.5456	0.9086
DaimlerChrysler AG	0.8673	0.9087	0.5865	1.2133	0.8892
Deutsche Bank AG	0.8357	0.8678	0.1442	1.1358	0.8888
Deutsche Telekom AG	0.7844	0.8637	0.4869	1.1095	0.8647
E.ON AG	0.8305	0.8465	0.0562	1.3062	0.8579
MRG AG	0.9148	0.9389	0.2384	1.2360	0.9017
SAP AG	0.8595	0.9745	0.7223	1.2156	0.9354
Siemens AG	0.8588	0.9146	0.5048	1.0653	0.8866
Volkswagen AG	0.7982	0.9184	0.2745	1.3300	0.8909
Average	0.8490	0.9056	0.3151	1.3582	0.8944

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta r(f,t) + \varepsilon t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - c

Hedge ratios - France

France					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
Alcatel SA	0.8450	0.9822	0.1168	1.4925	0.9725
Aventis SA	1.0003	0.9891	0.4486	1.1235	0.9792
Axa SA	0.8587	0.9468	0.7519	1.1606	0.9719
BNP Paribas SA	0.9516	0.9866	0.6890	1.2563	0.9793
Carrefour SA	0.9114	0.9488	0.7409	1.4743	0.9961
France Telecom SA	0.9984	1.0027	0.7372	1.2477	1.0114
Sanofi-Synthelabo SA	0.9419	0.9795	0.7739	1.2120	0.9732
Suez SA	1.0279	1.0266	0.7189	1.4746	0.9939
Total SA	0.9747	0.9857	0.8297	1.2366	0.9877
Vivendi Universal SA	0.9517	0.9339	0.6503	1.3358	0.9958
Average	0.9462	0.9782	0.6457	1.3014	0.9861

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - d

Hedge ratios - Italy

Italy					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
Assicurazioni Generali SpA	1.0161	1.0195	0.5520	1.2645	1.0105
Enel SpA	0.9107	0.9897	0.2173	1.3888	0.9513
Eni SpA	0.9901	0.9861	0.4579	1.2220	0.9982
MediaSet SpA	0.9167	0.9658	0.7546	1.0373	0.9284
San Paolo IMI SpA	0.9236	1.0054	0.7019	1.2098	1.0040
Telecom Italia Mobile SpA	0.9978	0.9882	0.4954	1.1779	0.9637
Telecom Italia SpA	1.0085	1.0105	0.3701	1.2408	0.9478
UniCredito Italiano SpA	0.9968	1.0085	0.6624	1.1974	0.9574
Average	0.9700	0.9967	0.5265	1.2173	0.9702

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon\, t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - e

Hedge ratios - Netherlands

Netherlands					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
ABN AMRO Holdings NV	1.0129	1.0105	0.3805	1.5051	0.9797
Aegon NV	0.9694	0.9860	0.7954	1.2461	0.9995
ING Groep NV	0.9487	0.9948	0.8066	1.2135	0.9920
Koninklijke Ahold NV	0.9624	0.9912	0.8297	1.3476	1.0230
Koninklijke Philips Electronics NV	0.9838	0.9800	0.8559	1.1434	1.0092
Royal Dutch Petroleum Co.	0.9905	1.0016	0.7581	1.2898	1.0030
Average	0.9780	0.9940	0.7377	1.2909	1.0011

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon\, t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - f

Hedge ratios - Switzerland

Switzerland					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
Crédit Suisse Group	0.9698	0.9855	0.7522	1.0823	0.9634
Nestle SA	0.9139	0.9306	0.3610	1.1854	0.9841
Novartis	0.9250	0.9560	0.6565	1.1126	0.9460
Roche Holdings AG	0.9511	0.9803	0.7785	1.1741	0.9628
UBS AG	0.9170	0.9944	0.5720	1.1087	0.9692
Average	0.9354	0.9694	0.6240	1.1326	0.9651

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - g

Hedge ratios - Sweden

Sweden					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
Hennes&Mauritz AB	0.7924	0.9680	0.6864	1.0952	0.9770
Nordea AB	0.9866	1.0065	0.2431	1.0975	0.9953
Svenska Handelsbanken	0.9662	0.9851	0.6054	1.1100	0.9862
T. LM Ericsson	0.9541	0.9962	0.9439	1.0281	0.9879
Average	0.9248	0.9890	0.6197	1.0827	0.9866

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE II - h

Hedge ratios - Spain

Spain					
Company	Risk-minimizing hedge ratio	Modified risk-minimizing hedge ratio	Daily GARCH hedge ratios		
			Minimum	Maximum	Average
BBVA SA	1.0039	1.0254	0.9078	1.2864	1.0128
Santander Central Hispano SA	0.9701	0.9611	0.8266	1.2296	0.9975
Telefonica SA	0.9829	0.9931	0.6072	1.1104	0.9713
Average	0.9856	0.9932	0.7805	1.2088	0.9939

Hedge ratios were computed with daily returns over the first year of data. The risk-minimizing hedge ratios were obtained with an OLS regression of the following equation: $r(s,t) = \alpha + \beta\, r(f,t) + \varepsilon\, t$. The modified risk-minimizing hedge ratios were obtained by excluding outliers which were more than three standard deviations from the mean and by applying the Hildreth-Lu procedure in order to eliminate the serial correlation of the residuals found in the basic OLS regression. The daily time-varying hedge ratios were computed via the GARCH (1,1) process with the daily returns of the preceding 250 days.

TABLE III - a

Regression coefficients and statistics - United Kingdom

	United Kingdom							
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Abbey National plc	0,0001	0,9269	0,87	2,8050	0,0004	0,9636	0,94	1,9163
AstraZeneca plc	0,0001	0,9819	0,79	3,0098	0,0001	0,9877	0,92	2,1298
Aviva plc	0,0001	0,9536	0,92	2,7959	0,0002	0,9250	0,95	1,9280
Barclays plc	0,0003	0,8832	0,75	2,8127	0,0001	0,9883	0,93	2,2816
BP plc	0,0001	0,9853	0,93	2,9849	0,0002	0,9767	0,96	2,1175
Diageo plc	0,0001	0,9729	0,91	3,0427	0,0001	0,9852	0,95	2,1932
GlaxoSmithKline plc	0,0001	1,0337	0,88	2,9502	0,0002	1,0416	0,92	2,1681
HBOS	0,0002	0,9737	0,91	2,9131	0,0003	0,9824	0,94	2,0002
HSBC Holdings plc	0,0002	1,0219	0,89	2,9513	0,0001	0,9708	0,95	2,2770
Legal&General Grp	0,0003	0,8510	0,79	2,7943	0,0001	0,9500	0,92	2,2585
Lloyds TSB Grp plc	0,0002	0,9444	0,84	2,9731	0,0001	0,9577	0,91	2,0790
Royal Bank Scotland	0,0002	0,9825	0,92	2,9499	0,0000	0,9855	0,95	2,1693
Sainsbury (J) plc	0,0001	1,0023	0,90	3,0166	0,0000	0,9943	0,93	2,0029
Shell T&T Co. plc	0,0001	0,8641	0,86	2,9131	0,0001	0,9781	0,95	2,2424
Tesco plc	0,0001	0,9692	0,92	2,8243	0,0001	0,9736	0,95	2,1928
Unilever plc	0,0001	0,9484	0,89	2,9752	0,0001	0,9429	0,94	2,1748
Vodafone Group plc	0,0001	0,9914	0,86	3,0143	-0,0001	1,0076	0,96	2,0219
Average	0,0001	0,9580	0,87	2,9251	0,0001	0,9771	0,94	2,1267

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - b

Regression coefficients and statistics - Germany

Company	Germany							
	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Allianz AG	0,0000	0,9247	0,87	2,8749	0,0001	0,9290	0,90	2,1661
BASF AG	0,0001	0,8799	0,78	2,6813	0,0005	0,8963	0,84	1,9669
Bayer AG	-0,0002	0,8324	0,75	2,7591	-0,0001	0,8940	0,85	2,1276
Bayerische H&V AG	-0,0003	0,8012	0,62	2,8253	0,0000	0,9145	0,75	2,0656
DaimlerChrysler AG	0,0000	0,8673	0,85	2,7933	-0,0001	0,9087	0,88	2,1192
Deutsche Bank AG	-0,0002	0,8357	0,83	2,5722	-0,0003	0,8678	0,91	2,0604
Deutsche Telekom	-0,0006	0,7844	0,71	2,9202	-0,0002	0,8637	0,80	2,1329
E.ON AG	0,0001	0,8305	0,77	2,8811	0,0001	0,8465	0,83	2,0247
MRG AG	-0,0001	0,9148	0,84	3,1884	-0,0002	0,9389	0,91	2,1110
SAP AG	-0,0001	0,8595	0,72	2,9091	-0,0002	0,9745	0,89	2,2421
Siemens AG	-0,0001	0,8588	0,83	2,9663	0,0000	0,9146	0,90	2,2912
Volkswagen AG	0,0002	0,7982	0,72	2,7698	0,0001	0,9184	0,86	2,2173
Average	-0,0001	0,8490	0,77	2,8451	0,0000	0,9056	0,86	2,1271

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - c

Regression coefficients and statistics - France

Company	France							
	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Alcatel SA	-0,0007	0,8450	0,79	2,8960	-0,0003	0,9822	0,96	2,1275
Aventis SA	0,0000	1,0003	0,93	3,0060	0,0001	0,9891	0,95	2,0827
Axa SA	0,0000	0,8587	0,81	2,8436	-0,0001	0,9468	0,94	2,1473
BNP Paribas SA	0,0000	0,9516	0,90	2,6879	0,0000	0,9866	0,94	2,1950
Carrefour SA	0,0000	0,9114	0,85	2,8462	-0,0001	0,9488	0,93	2,1642
France Telecom SA	0,0001	0,9984	0,91	2,9613	0,0002	1,0027	0,95	2,2233
Sanofi-Synthelabo	0,0000	0,9419	0,89	2,8231	0,0001	0,9795	0,93	1,9574
Suez SA	0,0002	1,0279	0,92	3,0988	0,0001	1,0266	0,95	1,9865
Total SA	0,0001	0,9747	0,87	2,9145	-0,0001	0,9857	0,92	2,2580
Vivendi Universal SA	-0,0001	0,9517	0,87	2,7304	0,0000	0,9339	0,94	1,9611
Average	0,0000	0,9462	0,87	2,8808	0,0000	0,9782	0,94	2,1103

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - d

Regression coefficients and statistics - Italy

Italy								
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Ass. Generali SpA	0,0001	1,0161	0,94	2,8484	0,0001	1,0195	0,96	2,0629
Enel SpA	0,0002	0,9107	0,74	2,8363	-0,0001	0,9897	0,90	2,1596
Eni SpA	0,0001	0,9901	0,90	2,7026	0,0002	0,9861	0,93	2,2099
MediaSet SpA	0,0001	0,9167	0,85	2,8399	0,0001	0,9658	0,91	2,0836
San Paolo IMI SpA	0,0000	0,9236	0,79	2,5535	0,0001	1,0054	0,89	2,2395
Telecom Italia Mobile	0,0000	0,9978	0,90	2,9196	-0,0001	0,9882	0,95	2,1700
Telecom Italia SpA	0,0001	1,0085	0,93	2,7535	0,0000	1,0105	0,96	2,1278
UniCredito Italiano	0,0001	0,9968	0,92	2,7867	-0,0001	1,0085	0,95	2,0275
Average	0,0001	0,9700	0,87	2,7801	0,0000	0,9967	0,93	2,1351

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - e

Regression coefficients and statistics - Netherlands

Netherlands								
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
ABN AMRO Hold.NV	0,0002	1,0129	0,90	2,7368	0,0002	1,0105	0,93	2,1266
Aegon NV	0,0001	0,9694	0,92	2,8052	0,0002	0,9860	0,95	2,1300
ING Groep NV	0,0001	0,9487	0,92	2,8743	0,0000	0,9948	0,96	2,2227
Koninklijke Ahold NV	0,0000	0,9624	0,89	2,8921	0,0000	0,9912	0,93	2,1799
K.Philips Electr. NV	0,0001	0,9838	0,94	3,0650	-0,0001	0,9800	0,97	2,2426
Royal Dutch Petro.	0,0001	0,9905	0,93	3,0243	0,0001	1,0016	0,97	2,2471
Average	0,0001	0,9780	0,92	2,8996	0,0001	0,9940	0,95	2,1915

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals.

regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - f

Regression coefficients and statistics - Switzerland

Switzerland								
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Crédit Suisse Group	0,0002	0,9698	0,92	2,8700	-0,0001	0,9855	0,96	2,2909
Nestle SA	0,0001	0,9139	0,83	2,8738	-0,0001	0,9306	0,86	2,1387
Novartis	0,0000	0,9250	0,91	2,9959	0,0000	0,9560	0,93	2,1501
Roche Holdings AG	0,0001	0,9511	0,91	2,9205	0,0000	0,9803	0,94	2,1908
UBS AG	0,0002	0,9170	0,90	2,5290	-0,0002	0,9944	0,96	2,1986
Average	0,0001	0,9354	0,89	2,8378	-0,0001	0,9694	0,93	2,1938

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - g

Regression coefficients and statistics - Sweden

Sweden								
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
Hennes&Mauritz AB	0,0000	0,7924	0,76	2,8994	0,0001	0,9680	0,95	2,2366
Nordea AB	0,0002	0,9866	0,93	2,9018	0,0001	1,0065	0,95	2,2441
S. Handelsbanken	0,0002	0,9662	0,93	2,6692	0,0001	0,9851	0,95	2,2184
T. LM Ericsson	-0,0003	0,9541	0,96	3,1134	0,0000	0,9962	0,98	2,1556
Average	0,0000	0,9248	0,90	2,8960	0,0001	0,9890	0,96	2,2137

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE III - h

Regression coefficients and statistics - Spain

Spain								
Company	Risk-minimizing hedge OLS regression				Modified risk-minimizing hedge OLS regression			
	alpha	beta	R squared	Durbin-Watson	alpha	beta	R squared	Durbin-Watson
BBVA SA	0,0001	1,0039	0,92	2,9006	0,0002	1,0254	0,94	2,1089
Santander Ctrl Hisp.	0,0001	0,9701	0,88	2,8990	0,0001	0,9611	0,91	2,3044
Telefonica SA	0,0001	0,9829	0,93	3,0780	-0,0001	0,9931	0,96	2,1155
Average	0,0001	0,9856	0,91	2,9592	0,0001	0,9932	0,94	2,1763

The alpha measure is the constant of the regression line, the beta figure represents the hedge ratio, the R squared statistic measures the goodness of fit of the regression line where higher values indicate a better fit and the Durbin-Watson test demonstrates if first-order serial correlation is present in the residuals. Values between 1.69 and 2.31 indicate no serial correlation.

TABLE IV - a

Diagnostic tests - United Kingdom

	United Kingdom								
	Augmented Dickey-Fuller						Ljung-Box Q statistic		
Company	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Abbey National plc	3	-6,95	1	-9,82	7	-7,16	42,02	49,19	88,90
AstraZeneca plc	1	-14,14	1	-13,25	12	-7,38	66,16	68,62	93,47
Aviva plc	3	-8,01	0	-16,64	3	-12,48	40,84	43,74	75,43
Barclays plc	3	-9,22	1	-11,63	8	-6,07	48,24	54,62	68,32
BP plc	4	-8,73	4	-8,54	5	-9,17	62,30	67,96	88,65
Diageo plc	0	-16,70	1	-12,22	3	-12,73	70,09	75,26	102,41
GlaxoSmithKline plc	1	-15,33	1	-14,39	5	-11,97	58,46	60,18	136,21
HBOS	13	-4,74	0	-15,26	3	-13,73	53,94	63,56	127,12
HSBC Holdings plc	7	-4,55	6	-5,25	3	-12,47	59,18	67,69	99,34
Legal&General Grp	0	-18,12	6	-4,80	1	-14,92	40,65	41,58	86,43
Lloyds TSB Grp plc	3	-9,49	7	-5,67	5	-10,54	60,74	99,13	116,57
Royal Bank Scotland	8	-3,93	8	-3,95	3	-11,63	77,27	83,30	116,76
Sainsbury (J) plc	7	-5,47	6	-5,52	4	-10,24	66,57	82,61	98,71
Shell T&T Co. plc	3	-8,00	2	-11,18	8	-5,51	56,82	57,95	89,87
Tesco plc	2	-11,94	2	-11,56	7	-8,05	44,90	46,14	116,17
Unilever plc	3	-7,09	3	-7,32	9	-6,06	61,83	64,17	93,78
Vodafone Group plc	1	-12,40	2	-10,07	10	-8,10	65,89	82,33	106,46
Average	4	-9,69	3	-9,83	6	-9,89	57,41	65,18	100,27

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - b

Diagnostic tests - Germany

Germany									
	Augmented Dickey-Fuller						Ljung-Box Q statistic		
Company	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Allianz AG	0	-15,01	2	-8,80	2	-15,53	49,65	60,74	110,28
BASF AG	6	-5,78	0	-15,70	5	-11,48	30,79	41,20	75,38
Bayer AG	6	-6,15	4	-8,46	5	-9,38	37,98	48,84	74,38
Bayerische H&V AG	0	-16,19	0	-16,58	7	-6,68	44,56	59,00	106,82
DaimlerChrysler AG	0	-13,88	0	-14,16	2	-13,69	40,46	44,26	88,56
Deutsche Bank AG	1	-11,85	11	-4,95	2	-15,02	21,20	36,98	61,59
Deutsche Telekom	0	-15,13	1	-11,76	2	-13,09	55,18	56,99	99,37
E.ON AG	0	-17,58	3	-9,70	2	-14,73	50,84	58,88	101,98
MRG AG	2	-8,49	2	-8,41	4	-9,93	89,84	133,68	185,87
SAP AG	1	-9,60	1	-10,06	7	-6,16	53,63	55,64	88,88
Siemens AG	0	-14,91	1	-12,14	2	-13,69	61,14	63,09	102,04
Volkswagen AG	0	-14,37	0	-16,38	1	-16,03	39,19	48,83	84,64
Average	1	-12,41	2	-11,43	3	-12,12	47,87	59,01	98,32

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - c

Diagnostic tests - France

France									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Alcatel SA	0	-15,46	0	-15,50	20	-2,77	51,39	62,38	153,69
Aventis SA	14	-4,04	19	-4,63	4	-11,20	65,59	76,44	92,88
Axa SA	0	-15,47	0	-15,72	3	-11,33	45,21	49,25	65,27
BNP Paribas SA	0	-15,17	0	-15,15	1	-15,44	31,87	32,83	56,06
Carrefour SA	0	-17,07	0	-16,45	4	-9,51	46,49	60,69	79,85
France Telecom SA	2	-8,60	2	-8,37	9	-8,41	59,33	63,32	95,43
Sanofi-Synthelabo	5	-8,43	4	-9,03	10	-7,56	45,04	46,77	96,30
Suez SA	19	-3,73	19	-3,88	8	-8,38	81,54	99,30	111,19
Total SA	0	-18,04	0	-16,68	9	-8,12	57,48	60,60	108,50
Vivendi Universal SA	0	-15,68	0	-15,43	13	-8,09	34,40	51,41	66,73
Average	4	-12,17	4	-12,08	8	-9,08	51,83	60,30	92,59

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - d

Diagnostic tests - Italy

Italy									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Ass. Generali SpA	0	-14,31	0	-13,93	13	-6,92	47,52	57,48	101,53
Enel SpA	2	-8,83	0	-18,17	8	-6,19	45,07	46,23	80,09
Eni SpA	0	-17,56	0	-16,62	1	-17,22	31,62	38,08	66,41
MediaSet SpA	3	-9,01	0	-15,72	5	-9,46	46,76	47,51	64,25
San Paolo IMI SpA	0	-16,59	0	-15,55	3	-11,36	19,73	30,34	42,07
Telecom Italia Mobile	2	-8,97	2	-8,38	3	-12,78	57,56	65,02	94,63
Telecom Italia SpA	3	-5,95	3	-5,73	3	-10,78	36,66	40,88	59,20
UniCredito Italiano	7	-5,37	5	-7,80	2	-13,19	39,67	42,87	74,37
Average	2	-10,82	1	-12,74	5	-10,99	40,57	46,05	72,82

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - e

Diagnostic tests - Netherlands

Netherlands									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
ABN AMRO Hold.NV	3	-7,20	2	-9,29	5	-9,79	35,49	54,60	75,25
Aegon NV	0	-16,37	5	-7,38	4	-10,79	41,40	44,81	64,68
ING Groep NV	14	-5,62	14	-5,56	4	-10,55	49,41	51,56	65,60
Koninklijke Ahold NV	0	-17,01	1	-10,40	3	-10,56	55,13	57,78	80,39
K.Philips Electr. NV	1	-13,50	1	-13,50	7	-8,95	72,28	75,22	106,26
Royal Dutch Petro.	4	-7,50	3	-7,68	6	-9,47	67,50	75,70	120,70
Average	4	-11,20	4	-8,97	5	-10,02	53,54	59,95	85,48

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - f

Diagnostic tests - Switzerland

Switzerland									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Crédit Suisse Group	4	-8,47	4	-8,50	7	-6,97	48,80	57,30	85,06
Nestle SA	2	-10,83	2	-10,69	11	-7,73	49,20	53,63	93,95
Novartis	0	-14,36	0	-14,75	4	-11,47	63,90	73,40	92,90
Roche Holdings AG	0	-14,50	0	-15,03	6	-9,90	54,82	60,88	84,71
UBS AG	2	-10,27	2	-10,09	13	-5,69	18,45	27,91	64,37
Average	2	-11,69	2	-11,81	8	-8,35	47,03	54,62	84,20

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - g

Diagnostic tests - Sweden

Sweden									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
Hennes&Mauritz AB	0	-17,73	0	-18,98	3	-11,08	52,00	54,76	68,49
Nordea AB	4	-8,63	4	-8,55	2	-13,67	52,10	52,57	101,58
S. Handelsbanken	0	-16,64	0	-16,84	2	-12,71	32,75	37,10	55,48
T. LM Ericsson	2	-10,21	2	-10,10	7	-5,82	79,37	93,69	135,85
Average	2	-13,30	2	-13,62	4	-10,82	54,06	59,53	90,35

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE IV - h

Diagnostic tests - Spain

Spain									
Company	Augmented Dickey-Fuller						Ljung-Box Q statistic		
	Lags	Spot	Lags	Futures	Lags	Residuals	1 Lag	5 Lags	24 Lags
BBVA SA	1	-12,16	0	-15,93	10	-7,71	52,14	63,04	119,16
Santander Ctrl Hisp.	0	-16,57	0	-15,67	8	-8,82	55,93	58,68	82,78
Telefonica SA	0	-15,42	0	-15,03	2	-14,85	77,04	87,00	122,90
Average	0	-14,72	0	-15,54	7	-10,46	61,70	69,57	108,28

The augmented Dickey-Fuller test is a measure of data stationarity. Values lower than the critical figures suggest that the data are stationary in nature. Critical values are -3.458 at the 1% level of significance, -2.874 at the 5% level of significance and -2.573 at the 10% level of significance. The Ljung-Box Q statistic is a measure of higher-order autocorrelation. Values higher than the critical figure indicate autocorrelation in the data series. Chi-square critical values at the 5% level of significance are 3.84 for 1 lag, 11.07 for 5 lags and 36.42 for 24 lags.

TABLE V - a

Portfolio variances - United Kingdom

	United Kingdom				
Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Abbey National plc	0,00073861	0,00006080	**0,00005771**	0,00005822	0,00006015
	(92,19%)	(5,07%)	(0,00%)	(0,88%)	(4,04%)
AstraZeneca plc	0,00073179	0,00005497	**0,00005443**	0,00005455	0,00005872
	(92,56%)	(1,00%)	(0,00%)	(0,23%)	(7,31%)
Aviva plc	0,00080949	0,00004671	0,00004345	**0,00004331**	0,00004464
	(94,65%)	(7,27%)	(0,31%)	(0,00%)	(2,98%)
Barclays plc	0,00098598	0,00007732	**0,00007365**	0,00007564	0,00007644
	(92,53%)	(4,74%)	(0,00%)	(2,63%)	(3,65%)
BP plc	0,00049639	**0,00001881**	0,00001884	0,00001896	0,00001951
	(96,21%)	(0,00%)	(0,19%)	(0,81%)	(3,61%)
Diageo plc	0,00027566	**0,00001921**	0,00001936	0,00001925	0,00001968
	(93,03%)	(0,00%)	(0,77%)	(0,18%)	(2,39%)
GlaxoSmithKline plc	0,00050126	**0,00002237**	0,00002448	0,00002515	0,00002581
	(95,54%)	(0,00%)	(8,63%)	(11,06%)	(13,34%)
HBOS	0,00046802	0,00003696	**0,00003588**	0,00003616	0,00003673
	(92,33%)	(2,95%)	(0,00%)	(0,79%)	(2,34%)
HSBC Holdings plc	0,00028910	0,00001977	0,00002079	0,00001887	**0,00001460**
	(94,95%)	(26,14%)	(29,76%)	(22,62%)	(0,00%)
Legal & General Grp plc	0,00089996	0,00006046	0,00007255	0,00006010	**0,00004526**
	(94,97%)	(25,13%)	(37,61%)	(24,70%)	(0,00%)
Lloyds TSB Group plc	0,00089077	0,00007180	0,00007069	**0,00007046**	0,00008753
	(92,09%)	(1,87%)	(0,33%)	(0,00%)	(19,50%)
Royal Bank of Scotland	0,00085457	0,00011054	0,00010987	0,00010995	**0,00006967**
	(91,85%)	(36,98%)	(36,59%)	(36,64%)	(0,00%)
Sainsbury (J) plc	0,00041128	0,00005686	0,00005692	0,00005674	**0,00005061**
	(87,69%)	(11,00%)	(11,09%)	(10,81%)	(0,00%)
Shell T&T Co. plc	0,00059522	0,00002907	0,00003631	0,00002875	**0,00002292**
	(96,15%)	(21,16%)	(36,87%)	(20,29%)	(0,00%)
Tesco plc	0,00032528	0,00004562	0,00004524	**0,00000000**	0,00003469
	(100,00%)	(100,00%)	(100,00%)	(0,00%)	(100,00%)
Unilever plc	0,00034082	0,00002155	0,00002237	0,00002255	**0,00001837**
	(94,61%)	(14,75%)	(17,88%)	(18,56%)	(0,00%)
Vodafone Group plc	0,00128737	0,00005190	0,00005195	0,00005200	**0,00004442**
	(96,55%)	(14,41%)	(14,50%)	(14,59%)	(0,00%)
Average	0,01090157	0,00080472	0,00081449	0,00075068	**0,00072975**
	(93,31%)	(9,32%)	(10,40%)	(2,79%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - b

Portfolio variances - Germany

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
	Germany				
Allianz AG	0,00148458	0,00037990	**0,00034966**	0,00035089	0,00045471
	(76,45%)	(7,96%)	(0,00%)	(0,35%)	(23,10%)
BASF AG	0,00051432	0,00010154	0,00009608	0,00009594	**0,00007528**
	(85,36%)	(25,86%)	(21,64%)	(21,53%)	(0,00%)
Bayer AG	0,00141399	0,00083223	0,00077813	0,00079092	**0,00027174**
	(80,78%)	(67,35%)	(65,08%)	(65,64%)	(0,00%)
Bayerische H&V AG	0,00210096	0,00049988	0,00050261	0,00048186	**0,00036972**
	(82,40%)	(26,04%)	(26,44%)	(23,27%)	(0,00%)
DaimlerChrysler AG	0,00086433	0,00019697	0,00017656	0,00017935	**0,00013867**
	(83,96%)	(29,60%)	(21,46%)	(22,68%)	(0,00%)
Deutsche Bank AG	0,00082398	0,00018799	0,00017286	0,00017212	**0,00009985**
	(87,88%)	(46,89%)	(42,24%)	(41,99%)	(0,00%)
Deutsche Telekom	0,00135073	0,00035625	0,00033426	0,00032724	**0,00025855**
	(80,86%)	(27,42%)	(22,65%)	(20,99%)	(0,00%)
E.ON AG	0,00066919	0,00013400	0,00012713	0,00012607	**0,00007934**
	(88,14%)	(40,79%)	(37,59%)	(37,06%)	(0,00%)
MRG AG	0,00159692	0,00028331	**0,00024767**	0,00025496	0,00027642
	(84,49%)	(12,58%)	(0,00%)	(2,86%)	(10,40%)
SAP AG	0,00089398	0,00017009	0,00017046	0,00016770	**0,00012796**
	(85,69%)	(24,77%)	(24,93%)	(23,70%)	(0,00%)
Siemens AG	0,00091631	0,00018821	0,00017294	0,00017433	**0,00013565**
	(85,20%)	(27,93%)	(21,56%)	(22,19%)	(0,00%)
Volkswagen AG	0,00090480	0,00018471	0,00017027	0,00016914	**0,00010890**
	(87,96%)	(41,04%)	(36,04%)	(35,62%)	(0,00%)
Average	0,01353409	0,00351508	0,00329863	0,00329052	**0,00239679**
	(82,29%)	(31,81%)	(27,34%)	(27,16%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - c
Portfolio variances - France

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			France		
Alcatel SA	0,00381798	0,00150303	0,00114778	0,00144892	**0,00015689**
	(95,89%)	(89,56%)	(86,33%)	(89,17%)	(0,00%)
Aventis SA	0,00052574	0,00009618	0,00009624	0,00009404	**0,00003753**
	(92,86%)	(60,98%)	(61,00%)	(60,09%)	(0,00%)
Axa SA	0,00221416	**0,00007577**	0,00011071	0,00007860	0,00008910
	(96,58%)	(0,00%)	(31,56%)	(3,60%)	(14,97%)
BNP Paribas SA	0,00120937	0,00006112	0,00006027	0,00006031	**0,00004464**
	(96,31%)	(26,95%)	(25,92%)	(25,97%)	(0,00%)
Carrefour SA	0,00095778	0,00008684	0,00009169	0,00008793	**0,00005808**
	(93,94%)	(33,12%)	(36,66%)	(33,95%)	(0,00%)
France Telecom SA	0,00330244	0,00013082	0,00013081	0,00013089	**0,00009994**
	(96,97%)	(23,61%)	(23,60%)	(23,65%)	(0,00%)
Sanofi-Synthelabo SA	0,00049965	0,00005307	0,00005272	0,00005258	**0,00004203**
	(91,59%)	(20,81%)	(20,28%)	(20,07%)	(0,00%)
Suez SA	0,00145232	0,00011071	0,00011243	0,00011230	**0,00006630**
	(95,43%)	(40,11%)	(41,03%)	(40,96%)	(0,00%)
Total SA	0,00047800	0,00003514	0,00003517	0,00003509	**0,00002432**
	(94,91%)	(30,78%)	(30,85%)	(30,68%)	(0,00%)
Vivendi Universal SA	0,00373085	0,00018828	0,00019790	0,00020557	**0,00013241**
	(96,45%)	(29,67%)	(33,09%)	(35,59%)	(0,00%)
Average	0,01818829	0,00234095	0,00203571	0,00230622	**0,00075125**
	(95,87%)	(67,91%)	(63,10%)	(67,43%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - d

Portfolio variances - Italy

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Italy		
Assicuraziono Generali	0,00071357	0,00006575	0,00006671	0,00006696	**0,00003850**
	(94,60%)	(41,45%)	(42,29%)	(42,50%)	(0,00%)
Enel SpA	0,00036960	0,00012349	0,00011240	0,00012188	**0,00004932**
	(86,66%)	(60,06%)	(56,12%)	(59,54%)	(0,00%)
Eni SpA	0,00042530	0,00007576	0,00007525	0,00007506	**0,00004911**
	(88,45%)	(35,18%)	(34,73%)	(34,57%)	(0,00%)
MediaSet SpA	0,00043274	0,00006194	0,00005541	0,00005843	**0,00004874**
	(88,74%)	(21,31%)	(12,04%)	(16,59%)	(0,00%)
San Paolo IMI SpA	0,00061818	0,00011008	0,00010424	0,00011078	**0,00007454**
	(87,94%)	(32,28%)	(28,49%)	(32,71%)	(0,00%)
Telecom Italia Mobile	0,00053716	0,00014827	0,00014775	0,00014555	**0,00008487**
	(84,20%)	(42,76%)	(42,56%)	(41,69%)	(0,00%)
Telecom Italia SpA	0,00040472	0,00010031	0,00010157	0,00010188	**0,00004583**
	(88,68%)	(54,31%)	(54,88%)	(55,01%)	(0,00%)
UniCredito Italiano SpA	0,00050996	0,00009952	0,00009932	0,00010010	**0,00007844**
	(84,62%)	(21,18%)	(21,02%)	(21,64%)	(0,00%)
Average	0,00401123	0,00078513	0,00076265	0,00078064	**0,00046936**
	(88,30%)	(40,22%)	(38,46%)	(39,88%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - e

Portfolio variances - Netherlands

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Netherlands		
ABN AMRO Holdings NV	0,00156691	0,00015696	0,00015876	0,00015839	**0,00009352**
	(94,03%)	(40,42%)	(41,09%)	(40,95%)	(0,00%)
Aegon NV	0,00266486	0,00013929	0,00013987	**0,00013896**	0,00014819
	(94,79%)	(0,24%)	(0,65%)	(0,00%)	(6,23%)
ING Groep NV	0,00155681	0,00009671	0,00009709	0,00009638	**0,00006571**
	(95,78%)	(32,05%)	(32,32%)	(31,82%)	(0,00%)
Koninklijke Ahold NV	0,00425370	0,00024918	0,00024788	**0,00024781**	0,00027525
	(94,17%)	(0,55%)	(0,03%)	(0,00%)	(9,97%)
Konin. Philips Electr. NV	0,00196589	**0,00005818**	0,00005879	0,00005908	0,00005984
	(97,04%)	(0,00%)	(1,03%)	(1,51%)	(2,76%)
Royal Dutch Petroleum	0,00052619	0,00002051	0,00002062	0,00002050	**0,00001387**
	(97,36%)	(32,35%)	(32,72%)	(32,32%)	(0,00%)
Average	0,01253436	0,00072083	0,00072301	0,00072112	**0,00065638**
	(94,76%)	(8,94%)	(9,22%)	(8,98%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - f

Portfolio variances - Switzerland

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Switzerland		
Crédit Suisse Group	0,00086373	0,00005464	0,00005147	0,00005290	**0,00003783**
	(95,62%)	(30,77%)	(26,50%)	(28,49%)	(0,00%)
Nestle SA	0,00022072	0,00005838	0,00005392	0,00005452	**0,00002965**
	(86,57%)	(49,21%)	(45,02%)	(45,61%)	(0,00%)
Novartis	0,00024137	0,00003772	0,00003628	0,00003655	**0,00002793**
	(88,43%)	(25,97%)	(23,03%)	(23,59%)	(0,00%)
Roche Holdings AG	0,00032012	0,00003262	0,00003080	0,00003169	**0,00002230**
	(93,03%)	(31,63%)	(27,59%)	(29,63%)	(0,00%)
UBS AG	0,00038711	0,00003102	0,00002972	0,00003076	**0,00002058**
	(94,68%)	(33,64%)	(30,73%)	(33,07%)	(0,00%)
Average	0,00203305	0,00021438	0,00020219	0,00020641	**0,00013829**
	(93,20%)	(35,49%)	(31,60%)	(33,00%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - g

Portfolio variances - Sweden

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Sweden		
Hennes&Mauritz AB	0,00029883	0,00002557	0,00003288	0,00002501	**0,00001893**
	(93,66%)	(25,98%)	(42,42%)	(24,31%)	(0,00%)
Nordea AB	0,00048344	0,00006895	0,00006821	0,00006937	**0,00004034**
	(91,66%)	(41,50%)	(40,86%)	(41,85%)	(0,00%)
Svenska Handelsbanken	0,00025397	0,00003280	0,00003249	0,00003259	**0,00002655**
	(89,55%)	(19,05%)	(18,28%)	(18,55%)	(0,00%)
T. LM Ericsson	0,00184412	0,00005683	0,00006066	0,00005686	**0,00005330**
	(97,11%)	(6,21%)	(12,13%)	(6,27%)	(0,00%)
Average	0,00288036	0,00018415	0,00019423	0,00018384	**0,00013912**
	(95,17%)	(24,46%)	(28,38%)	(24,33%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE V - h

Portfolio variances - Spain

Company	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Spain		
BBVA SA	0,00103887	0,00007022	0,00007012	0,00007009	**0,00005860**
	(94,36%)	(16,55%)	(16,43%)	(16,40%)	(0,00%)
Santander Ctrl Hispano	0,00100741	0,00005848	0,00006045	0,00006135	**0,00003971**
	(96,06%)	(32,10%)	(34,30%)	(35,27%)	(0,00%)
Telefonica SA	0,00078959	0,00009179	0,00008982	0,00009094	**0,00005761**
	(92,70%)	(37,24%)	(35,86%)	(36,65%)	(0,00%)
Average	0,00283587	0,00022050	0,00022038	0,00022238	**0,00015591**
	(94,50%)	(29,29%)	(29,25%)	(29,89%)	(0,00%)

This table shows the portfolio variance of returns over the second year of data. Numbers in bold indicate the lowest variance for each company. Values between parentheses represent the percentage increase in portfolio variance relative to the portfolio with the lowest variance.

TABLE VI - a

Significance of portfolio variances - all countries

	All countries				
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		62,2567	64,5683	63,2359	73,0249
		(0,0000)	(0,0000)	(0,0000)	(0,0000)
Naive 1:1 hedge	62,2567		0,0570	0,0183	3,2316
	(0,0000)		(0,8117)	(0,8927)	(0,0746)
Risk-minimizing hedge	64,5683	0,0570		0,0093	3,1762
	(0,0000)	(0,8117)		(0,9234)	(0,0771)
Modified risk-minimizing hedge	63,2359	0,0183	0,0093		2,8355
	(0,0000)	(0,8927)	(0,9234)		(0,0946)
Daily GARCH hedge	73,0249	3,2316	3,1762	2,8355	
	(0,0000)	(0,0746)	(0,0771)	(0,0946)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
All countries All ratios	65	58,9947	0,00000000	2,3999	3,9151

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - b

Significance of portfolio variances - United Kingdom

Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
	United Kingdom				
Unhedged portfolio		71,5798	71,4598	72,2588	72,7757
		(0,0000)	(0,0000)	(0,0000)	(0,0000)
Naive 1:1 hedge	71,5798		0,0045	0,1256	0,2963
	(0,0000)		(0,9468)	(0,7254)	(0,5900)
Risk-minimizing hedge	71,4598	0,0045		0,1779	0,3861
	(0,0000)	(0,9468)		(0,6760)	(0,5388)
Modified risk-minimizing hedge	72,2588	0,1256	0,1779		0,0211
	(0,0000)	(0,7254)	(0,6760)		(0,8853)
Daily GARCH hedge	72,7757	0,2963	0,3861	0,0211	
	(0,0000)	(0,5900)	(0,5388)	(0,8853)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
United Kingdom All ratios	17	70,4688	0,00000000	2,4859	4,1491

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - c

Significance of portfolio variances - Germany

	Germany				
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		32,9952	34,9898	34,9996	45,6057
		(0,0000)	(0,0000)	(0,0000)	(0,0000)
Naive 1:1 hedge	32,9952		0,0485	0,0519	1,8057
	(0,0000)		(0,8278)	(0,8218)	(0,1927)
Risk-minimizing hedge	34,9898	0,0485		0,0001	1,2621
	(0,0000)	(0,8278)		(0,9933)	(0,2734)
Modified risk-minimizing hedge	34,9996	0,0519	0,0001		1,2320
	(0,0000)	(0,8218)	(0,9933)		(0,2790)
Daily GARCH hedge	45,6057	1,8057	1,2621	1,2320	
	(0,0000)	(0,1927)	(0,2734)	(0,2790)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Germany All ratios	12	26,3299	0,00000000	2,5397	4,3009

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - d

Significance of portfolio variances - France

France					
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		12,3691	13,4360	12,5167	16,6000
		(0,0025)	(0,0018)	(0,0024)	(0,0007)
Naive 1:1 hedge	12,3691		0,0298	0,0003	1,2474
	(0,0025)		(0,8649)	(0,9861)	(0,2787)
Risk-minimizing hedge	13,4360	0,0298		0,0246	1,4463
	(0,0018)	(0,8649)		(0,8772)	(0,2447)
Modified risk-minimizing hedge	12,5167	0,0003	0,0246		1,2899
	(0,0024)	(0,9861)	(0,8772)		(0,2710)
Daily GARCH hedge	16,6000	1,2474	1,4463	1,2899	
	(0,0007)	(0,2787)	(0,2447)	(0,2710)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
France All ratios	10	11,5354	0,00000000	2,5787	4,4139

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - e

Significance of portfolio variances - Italy

Italy					
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		88,0776	89,4614	88,4063	110,4212
		(0,0000)	(0,0000)	(0,0000)	(0,0000)
Naive 1:1 hedge	88,0776		0,0364	0,0014	10,4560
	(0,0000)		(0,8515)	(0,9703)	(0,0060)
Risk-minimizing hedge	89,4614	0,0364		0,0235	9,2146
	(0,0000)	(0,8515)		(0,8804)	(0,0089)
Modified risk-minimizing hedge	88,4063	0,0014	0,0235		10,2812
	(0,0000)	(0,9703)	(0,8804)		(0,0063)
Daily GARCH hedge	110,4212	10,4560	9,2146	10,2812	
	(0,0000)	(0,0060)	(0,0089)	(0,0063)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Italy All ratios	8	82,2441	0,00000000	2,6415	4,6001

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - f

Significance of portfolio variances - Netherlands

Netherlands					
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		14,4228	14,4180	14,4228	14,5625
		(0,0035)	(0,0035)	(0,0035)	(0,0034)
Naive 1:1 hedge	14,4228		0,0001	0,0000	0,0459
	(0,0035)		(0,9939)	(0,9992)	(0,8347)
Risk-minimizing hedge	14,4180	0,0001		0,0000	0,0492
	(0,0035)	(0,9939)		(0,9947)	(0,8289)
Modified risk-minimizing hedge	14,4228	0,0000	0,0000		0,0465
	(0,0035)	(0,9992)	(0,9947)		(0,8336)
Daily GARCH hedge	14,5625	0,0459	0,0492	0,0465	
	(0,0034)	(0,8347)	(0,8289)	(0,8336)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Netherlands All ratios	6	14,2709	0,00000000	2,7587	4,9646

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - g

Significance of portfolio variances - Switzerland

	Switzerland				
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		9,4728	9,6045	9,5600	10,2992
		(0,0152)	(0,0147)	(0,0148)	(0,0124)
Naive 1:1 hedge	9,4728		0,1009	0,0428	5,5327
	(0,0152)		(0,7589)	(0,8412)	(0,0465)
Risk-minimizing hedge	9,6045	0,1009		0,0134	4,5694
	(0,0147)	(0,7589)		(0,9106)	(0,0650)
Modified risk-minimizing hedge	9,5600	0,0428	0,0134		5,1452
	(0,0148)	(0,8412)	(0,9106)		(0,0530)
Daily GARCH hedge	10,2992	5,5327	4,5694	5,1452	
	(0,0124)	(0,0465)	(0,0650)	(0,0530)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Switzerland All ratios	5	9,6950	0,00015801	2,8661	5,3176

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - h

Significance of portfolio variances - Sweden

	Sweden				
Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
Unhedged portfolio		3,1783	3,1550	3,1790	3,2864
		(0,1249)	(0,1260)	(0,1249)	(0,1198)
Naive 1:1 hedge	3,1783		0,0335	0,0000	0,7888
	(0,1249)		(0,8607)	(0,9959)	(0,4086)
Risk-minimizing hedge	3,1550	0,0335		0,0349	1,3173
	(0,1260)	(0,8607)		(0,8580)	(0,2948)
Modified risk-minimizing hedge	3,1790	0,0000	0,0349		0,7586
	(0,1249)	(0,9959)	(0,8580)		(0,4172)
Daily GARCH hedge	3,2864	0,7888	1,3173	0,7586	
	(0,1198)	(0,4086)	(0,2948)	(0,4172)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Sweden All ratios	4	3,1945	0,04378000	3,0556	5,9874

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VI - i

Significance of portfolio variances - Spain

Portfolios	Unhedged portfolio	Naive 1:1 hedge	Risk-minimizing hedge	Modified risk-minimizing hedge	Daily GARCH hedge
			Spain		
Unhedged portfolio		121,8323	122,2438	122,0114	129,1132
		(0,0004)	(0,0004)	(0,0004)	(0,0003)
Naive 1:1 hedge	121,8323		0,0001	0,0023	3,4896
	(0,0004)		(0,9978)	(0,9641)	(0,1351)
Risk-minimizing hedge	122,2438	0,0001		0,0029	4,1106
	(0,0004)	(0,9978)		(0,9595)	(0,1125)
Modified risk-minimizing hedge	122,0114	0,0023	0,0029		4,2809
	(0,0004)	(0,9641)	(0,9595)		(0,1073)
Daily GARCH hedge	129,1132	3,4896	4,1106	4,2809	
	(0,0003)	(0,1351)	(0,1125)	(0,1073)	

Category	Number of companies	F Statistic	P-Value	F critical value for all ratios at .05	F critical value for two ratios at .05
Spain All ratios	3	119,7362	0,00000000	3,4780	7,7086

The upper section of the table indicates the F statistic when comparing the portfolio variances with one another. Values between parentheses represent the p-values. The lower the p-value, the greater the probability that the variances are not equal.

TABLE VII - a

Portfolio Utility - United Kingdom

United Kingdom					
Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Abbey National plc	0,0366	0,0348	0,0357	0,0287	N/A
AstraZeneca plc	0,0258	0,0365	0,0451	0,0360	N/A
Aviva plc	0,0307	0,0307	0,0393	0,0430	0,0000925
Barclays plc	0,0324	0,0324	0,0298	0,0603	0,0006975
BP plc	0,0267	0,0267	0,0202	0,0170	N/A
Diageo plc	0,0402	0,0402	0,0401	0,0417	0,0000375
GlaxoSmithKline plc	0,0298	0,0298	0,0434	0,0481	0,0001175
HBOS	0,0406	0,0406	0,0415	0,0402	N/A
HSBC Holdings plc	0,0347	0,0347	0,0314	0,0261	N/A
Legal & General Grp plc	0,0599	0,0599	0,0637	0,0380	N/A
Lloyds TSB Group plc	0,0792	0,0792	0,0540	0,0409	N/A
Royal Bank of Scotland	0,0315	0,0315	0,0297	0,0098	N/A
Sainsbury (J) plc	0,0532	0,0532	0,0536	0,0587	0,0001275
Shell T&T Co. plc	0,0319	0,0319	0,0281	0,0309	N/A
Tesco plc	0,0240	0,0240	0,0300	0,0336	0,0000675
Unilever plc	0,0302	0,0302	0,0192	0,0290	N/A
Vodafone Group plc	0,0192	0,0192	0,0203	0,0150	N/A
Average	0,0369	0,0374	0,0368	0,0351	0,0001900

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - b

Portfolio Utility - Germany

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Germany					
Allianz AG	-0,0102	-0,1113	-0,1055	-0,0235	N/A
BASF AG	0,0398	0,0563	0,0541	0,0656	0,0002325
Bayer AG	0,0787	0,1087	0,0977	0,1302	0,0005375
Bayerische H&V AG	0,0003	-0,1744	-0,0747	-0,0611	N/A
DaimlerChrysler AG	0,0446	-0,0207	-0,0003	-0,0073	N/A
Deutsche Bank AG	0,0097	-0,0707	-0,0550	-0,0535	N/A
Deutsche Telekom	0,0363	0,0123	0,0212	0,0234	N/A
E.ON AG	0,0423	0,0121	0,0150	0,0430	0,0000175
MRG AG	-0,0179	-0,1068	-0,0816	-0,0668	N/A
SAP AG	0,0206	0,1011	0,0352	0,0625	N/A
Siemens AG	0,0333	-0,0364	-0,0088	-0,0267	N/A
Volkswagen AG	0,0240	-0,0631	-0,0112	-0,0231	N/A
Average	0,0251	-0,0244	-0,0095	0,0052	0,0002625

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - c

Portfolio Utility - France

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
France					
Alcatel SA	-0,1609	-0,2154	-0,1671	-0,1928	N/A
Aventis SA	0,0069	0,0069	0,0052	0,0086	0,0000425
Axa SA	0,0152	-0,0475	-0,0083	0,0149	N/A
BNP Paribas SA	0,0462	0,0361	0,0434	0,0553	0,0002275
Carrefour SA	0,0208	0,0126	0,0161	0,0228	0,0000500
France Telecom SA	0,0663	0,0660	0,0668	0,0581	N/A
Sanofi-Synthelabo SA	0,0213	0,0174	0,0199	0,0132	N/A
Suez SA	0,0419	0,0434	0,0433	0,0356	N/A
Total SA	0,0237	0,0186	0,0208	0,0272	0,0000875
Vivendi Universal SA	0,0338	0,0205	0,0156	0,0589	0,0006275
Average	0,0115	-0,0041	0,0056	0,0102	0,0002070

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - d

Portfolio Utility - Italy

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Italy					
Assicuraziono Generali	0,0191	0,0245	0,0256	0,0433	0,0004425
Enel SpA	0,0542	0,0355	0,0520	0,0230	N/A
Eni SpA	0,0481	0,0477	0,0476	0,0557	0,0001900
MediaSet SpA	0,0213	0,0451	0,0311	0,0437	N/A
San Paolo IMI SpA	0,0420	0,0806	0,0392	0,0353	N/A
Telecom Italia Mobile	0,1118	0,1111	0,1080	0,0818	N/A
Telecom Italia SpA	0,0534	0,0580	0,0591	0,0129	N/A
UniCredito Italiano SpA	0,0230	0,0219	0,0260	0,0088	N/A
Average	0,0466	0,0531	0,0486	0,0381	0,0003163

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - e

Portfolio Utility - Netherlands

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Netherlands					
ABN AMRO Holdings NV	0,0551	0,0568	0,0564	0,0810	0,0006050
Aegon NV	0,0747	0,0541	0,0652	0,0287	N/A
ING Groep NV	0,0366	0,0130	0,0342	0,0406	0,0001000
Koninklijke Ahold NV	0,0363	0,0044	0,0288	0,0545	0,0004550
Konin. Philips Electr. NV	0,0283	0,0196	0,0176	0,0409	0,0003150
Royal Dutch Petroleum	0,0323	0,0292	0,0328	0,0316	N/A
Average	0,0439	0,0295	0,0392	0,0462	0,0003688

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - f

Portfolio Utility - Switzerland

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Switzerland					
Crédit Suisse Group	-0,0049	0,0153	0,0048	0,0249	0,0002400
Nestle SA	0,0271	0,0243	0,0248	0,0354	0,0002075
Novartis	0,0206	0,0151	0,0174	0,0169	N/A
Roche Holdings AG	0,0120	0,0167	0,0139	0,0196	0,0000725
UBS AG	0,0249	0,0413	0,0260	0,0505	0,0002300
Average	0,0159	0,0225	0,0174	0,0295	0,0001875

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - g

Portfolio Utility - Sweden

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Sweden					
Hennes&Mauritz AB	0,0267	0,0289	0,0271	0,0315	0,0000650
Nordea AB	0,0490	0,0534	0,0469	0,0407	N/A
Svenska Handelsbanken	0,0293	0,0370	0,0327	0,0297	N/A
T. LM Ericsson	0,0011	0,0407	0,0044	0,0151	N/A
Average	0,0265	0,0400	0,0278	0,0293	0,0000650

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

TABLE VII - h

Portfolio Utility - Spain

Company	Naive 1:1 hedge	Risk-minimizing	Modified risk-minimizing	Daily GARCH hedge	Transaction costs
Spain					
BBVA SA	0,0423	0,0436	0,0510	0,0393	N/A
Santander Ctrl Hispano	0,0433	0,0357	0,0335	0,0411	N/A
Telefonica SA	0,0098	0,0056	0,0081	0,0182	0,0002525
Average	0,0318	0,0283	0,0309	0,0329	0,0003

This table shows the utility values calculated with the following formula: U = ((spot return – β (futures return)) – 4 (variance of the portfolio)). The transaction costs figure is provided when the utility of the GARCH hedge is highest and it represents the percentage commission that would equate the GARCH hedge and the next best hedge according to the following formula: Utility of next best hedge – 12 c = Utility of the GARCH hedge – 52 c, where c is the commission cost.

9. APPENDIX

9.1 The bivariate GARCH (1,1) computer program

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***************************************************************************************
*                                                                                     *
*DYNAMIC BIVARIATE GARCH(1.1)                                                         *
*                                                                                     *
*                                                                                     *
*                                                                                     *
*                                                                                     *
*                                                                                     *
*                                                                                     *
***************************************************************************************

ALL 510
OPEN DATA allianzdata.xls
DATA(format=xls,org=col)

*DECLARATION OF ELEMENTS

DEC VECT [series] A(2) Y(2) U(2)
DEC VECT [FRML] RESID(2)
DEC VECT C(1) D(600) E(1) F(600)
DECLARE  SYMM[SERIES] H(2,2)
DECLARE  FRML[SYMM] HF
DECLARE  SYMM HX(2,2) HIJF(2,2)
DECLARE  VECTOR UX
DECLARE  SYMM VC(2,2) VA(2,2) VB(2,2)
DECLARE  VECTOR[series] H12F(1) H22F(1) HRATIOS(300)


SET A(1) = lnat
SET A(2) = lnatf


*INTRODUCTION OF DAILY LOOP OVER 250 DAYS

COMPUTE  INI_ROW=3
COMPUTE  ITRR=INI_ROW
COMPUTE  WW=250
COMPUTE  Z =1

* INI_ROW = DATABASE STARTING ROW
* ITRR    = ITERATION VALUE
* WW      = WINDOW WIDTH

* ITERATION OF WINDOW LOOPS (1 to 249 WINDOWS= 500 DAYS)

DO k=0,249
   DO j=1,WW
        COMPUTE  C=%XROW(A(1),ITRR)
```

```
        COMPUTE  D(ITRR)=C(1)
        COMPUTE  E=%XROW(A(2),ITRR)
        COMPUTE  F(ITRR)=E(1)
                DISPLAY D(ITRR)
        COMPUTE  ITRR=ITRR+1

  END DO j

        COMPUTE  ITRR=(ITRR-WW)+1
        SET Y(1) = D(t)
        SET Y(2) = F(t)


        COMPUTE GSTART=ITRR , GEND=ITRR+(WW-1)

* GARCH REGRESSIONS AND COVARIANCE MATRIX

        NONLIN(parmset=meanparms) b11 b21
        FRML RESID1 = (Y(1)-b11)
        FRML RESID2 = (Y(2)-b21)

        LINREG(NOPRINT) Y(1) / U(1)
        # CONSTANT
        COMPUTE b11 = %BETA(1)

        LINREG(NOPRINT) Y(2) / U(2)
        # CONSTANT
        COMPUTE b21 = %BETA(1)

        VCV(MATRIX=RR,NOPRINT)
        # U



        DO i=1,2
                DO j=1,i
                        SET H(i,j)  = RR(i,j)
                END DO j
        END DO i

* ACCOUNT FOR CONDITIONAL STUDENT-T DISTRIBUTION

        SET U1 = 0.0
        SET U2 = 0.0
        COMPUTE  NU=3.0, K=2
        FRML LOGL = $
                U1 = RESID1(T) , U2 =RESID2(T) , $
         HIJF = HF(T), $
                HX = HF(T), $
                UX = ||U1(T),U2(T)||, $
                0.5*NU*LOG(NU)+%LNGAMMA(0.5*(NU+K))-%LNGAMMA(0.5*NU) $
                -0.5*LOG(%DET(((NU-2)/NU)*HX))-0.5*(NU+K)*LOG(NU+%QFORM(INV(((NU-
2)/NU)*HX),UX))
```

```
* GARCH (1,1) FORMULA

        NONLIN (ADD) NU
        NONLIN (parmset=garchparms) VC VA VB
        FRML HF = ||VC(1,1)+VA(1,1)*H(1,1){1}+VB(1,1)*U1{1}**2|$
        VC(1,2)+VA(1,2)*H(1,2){1}+VB(1,2)*U1{1}*U2{1},$
        VC(2,2)+VA(2,2)*H(2,2){1}+VB(2,2)*U2{1}**2||


* INITIALIZATION OF GARCH PARAMETERS

COMPUTE VC = RR ,VB=%MSCALAR(0.05),VA=%MSCALAR(0.05)

* ITERATIONS OF GARCH PROCESS

        NLPAR(SUBITS=50)
        MAXIMIZE(parmset=meanparms+garchparms,METHOD=SIMPLEX,RECURSIVE,ITERS=10)
LOGL GSTART GEND
        MAXIMIZE(parmset=meanparms+garchparms,METHOD=BFGS,ITERS=200) LOGL GSTART
GEND

* COMPUTATION OF HEDGE RATIOS

     SET H12F(1) = HIJF(1,2)
     SET H22F(1) = HIJF(2,2)
     COMPUTE aa = %XROW(H12F(1),1)
     COMPUTE bb = %XROW(H22F(1),1)
     COMPUTE HRATIO = aa(1) / bb(1)
     SET HRATIOS(z) = HRATIO
     COMPUTE Z = Z + 1


END DO k

OPEN COPY HRATIOS; COPY(FORMAT=XLS,ORG=OBS) 1 1 HRATIOS ; CLOSE COPY
```