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ABSTRACT

The objective of this paper is to estimate the hedge ratios of foreign-listed single stock futures (SSFs) and to compare the performance of risk reduction of different methods. The OLS method and a bivariate GJR-GARCH model are employed to estimate constant optimal hedge ratios and the dynamic hedging ratios, respectively. Data of the SSFs listed on the London International Financial Future and Options Exchange (LIFFE) are used in this research. We find that the data series have high estimated constant optimal hedge ratios and high constant correlation in the bivariate GJR- GARCH model, except for three SSFs with their underlying stocks traded in Italy. Our findings provide evidence that distance is a critical factor when explaining investor's trading behavior. Results also show that in general, of the three methods examined (i.e., naïve hedge, conventional OLS method, and dynamic hedging) the dynamic hedging performs the best and that naïve hedge is the worst.

Keywords: Hedging; GJR-GARCH; Hedge ratios; SSFs; Single stock futures; LIFFE; USFs

Introduction

Since the trading of futures has become more frequent in recent years, there has been much attention given to the issue of hedging with futures.

Many studies have dealt with the issue of hedging with various futures, such as commodity futures, currency futures, index futures, and so on (e.g., Baillie and Myers, 1991; Kroner and Sultan, 1993; Park and Switzer, 1995, respectively). However, studies on hedging with the newly invented futures contracts, single stock futures (SSFs), are rare. SSFs provide several advantages for investors. For instance, investors hedging with SSFs could efficiently reduce tracking error, because investors can hedge with a particular instrument rather than a rough index. In addition, SSFs are cost effective for investors. The strategy of longing a call and shorting a put option is now achieved by longing a single stock future. Since SSFs were designed for investors to manage firm-specific risk in their stocks, the underlying stock markets could be very sensitive to SSF contracts. As a result, the interesting issue of hedging with SSFs is no longer being neglected.

Although SSFs or individual stock futures (ISFs) have had leading roles in some studies (e.g., McKenzie, Brailsford, and Faff, 2000), most studies have focused on examining the impact of the domestic listed SSFs on their underlying stock markets. As the internationalization of worldwide financial markets becomes ever more rapid, firms have increasingly chosen to list their securities in foreign countries. Following this trend, numerous studies have been devoted to the effect of foreign listing. A growing amount of behavioral finance literature is available on the issue of "twin-securities". For example, Froot and Dabora (1998) provided evidence to challenge the efficient markets hypothesis, finding that fundamentally identical securities traded at disparate prices. Worldwide evidence has shown that the cumulated abnormal returns of the domestic firms are significantly influenced by their stocks that were listed in foreign exchanges after overseas listing (e.g., Foerster and Karolyi, 1993; Damodaran et al., 1993; Foerster and Karolyi, 1996). Besides, much research has been done on the influence of such regional factors as language, culture, and distance on the phenomenon of "home bias." For example, Grinblatt and Keloharju (2001) concluded that the Finnish are prone to trade stocks of domestic firms that communicate in the same language with them, that are located near them, and whose CEOs are of identical culture background. While much work has been done on the relationship between foreign and domestic stock markets, there has been little attention given to the connection between foreign listed derivatives and their domestic underlying markets. Moreover, there has been little literature on the issue of hedging with foreign listed futures.

Many theoretical methods have been used in previous studies to estimate the optimal hedge ratios. Chen, Lee, and Shrestha (2003) gave a clear summary of various methods. We summarize several important methods in Section 3. The conventional Ordinary Least Squares (OLS) approach is easy to apply but is criticized for its assumption of constant second moments. Thus, considering the features of heteroscedastic and leptokurtosis in time series data, many studies have gradually employed bivariate GARCH models to estimate time-varying hedge ratios.

The purpose of this paper is to estimate the hedge ratios of foreign-listed single stock futures (SSFs) and to compare the hedging performances of different methods.

The organization of this paper is as follows: a short report on the present situation of global SSFs markets is provided in Section 2; a brief literature review of hedge ratios is summarized in Section 3; the methodology employed is described in Section 4; the data and empirical results are described in Section 5, and the conclusions of the paper are presented in the final section.

2. Global SSFs Markets

We focused on the SSFs listed on the London International Financial Future and Options Exchange (LIFFE) in the United Kingdom; however, several exchanges other than LIFFE have SSFs listed. We give a short report on the present situation of worldwide SSFs markets in this section. Table 1 demonstrates a summary of the contract specifications of different exchanges.

TABLE 1 ABOUT HERE

2.1 The United Kingdom

As of June 23, 2003, LIFFE had SSFs traded on 116 individual stocks. The annual trading volumes of total SSFs listed on the LIFFE for 2001 and 2002 are 2325744 and 3935121 contracts, respectively. Each SSF represents 100 shares of the underlying stock in Europe (except for Italy and England), or 1000 shares of the underlying stock in Italy, the United States, and England. The contracts have delivery dates of two consecutive months or two near quarter months. The contracts are settled in cash. In addition, there are no specific daily price movement limits or position limits. Refer to **www.liffe.com** for more details.

2.2 The United States

The Commodity Futures Modernization Act of 2000 (CFMA) allows the U.S. securities and futures exchanges to trade SSFs. SSFs are restricted to regulation by both the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC). As of June 19, 2003, there have been 99 and 92 SSFs listed on NQLX and OneChicago, respectively. NQLX is a joint venture between NASDAQ/American Stock Exchange and LIFFE. OneChicago is a joint venture between the Chicago Board of Trade, Chicago Mercantile Exchange, and Chicago Board of Options Exchange. The top five SSFs listed on the NQLX by volume in March, 2003 are iShares Russell 2000 (IWM), NASDAQ-100 Index Tracking Stock (QQQ), KLA-Tencor Corporation (KLAC), Microsoft Corporation (MSFT), and Exxon Mobile Corporation (XOM) in order. The first 21 SSFs began trading on the OneChicago in November 8, 2002, and obtained trading volumes of 184081 contracts for 2002. Each SSF represents 100 shares of the underlying stock. The contracts have delivery dates of two near term serial months and two quarterly months. They are settled in physical delivery of underlying security on the third business day following the expiration day. There are no specific daily price movement limits. Refer to **www.nqlx.com** and **www.onechicago.com** for more details.

2.3 Australia

As of May 5, 2003, there have been 39 individual share futures (ISFs) listed on the Sydney Futures Exchange (SFE). Their underlying stocks are those listed on the Australian Stock Exchange. The annual trading volumes for1999, 2000, and 2001 were 8726, 8817, and 12545 contracts, respectively. Except that the ISFs on Telstra

Corporation deliver monthly up to 12 months ahead, other contracts have delivery dates of four quarterly months. Each ISF represents 1000 shares of the underlying stock except for Ansell ISF contracts, each which represent 200 shares of the underlying stock. Except that the ISFs on Telstra Corporation are settled in cash, other ISFs listed on SFE are settled in physical delivery of underlying security at the expiration day. The minimum price movement is set be the contract unit multiplied by 1 cent of A$. Refer to **www.sfe.com.au** for more details.

2.4 Spain

MEFF, the Spanish official exchange for futures and options, has listed nine SSFs up to now. The first batch of SSFs was introduced in January 2001 and reached trading volumes of 8766165 contracts in the entire year. Each SSF represents 100 shares of the underlying stock. In general, the contracts have delivery dates of four quarterly months; however, other expiration months not included in the quarterly months may also be introduced if needed. Contract holders can choose between physical delivery of underlying security and cash for the difference with respect to the reference price, which refers to the closing price of the stock on the expiration day. The minimum price fluctuation is the contract unit multiplied by 1 cent of EURO, while the maximum price movement is of no regulation. Refer to **www.meff.com** for more details.

2.5 Portugal

Portugal is still in the developing stage of the new derivatives products, SSFs. Since the launch of the first of the SSFs, Portugal Telecom futures, there have been seven SSFs listed on the Euronext Lisbon. The underlying stocks are Portugal Telecom, EDP, BCP, Cimpor, PT Multimédia, Sonae, and Telecel. Each SSF represents 100 shares of the underlying stock. The contracts have delivery dates of the current month, the following calendar month and the two closest months of March, June, September and December. The settlement at expiration date is made through physical delivery. Refer to **www.euronext.pt** for more details.

3. Brief Literature Review of Hedge Ratios

In this section, we briefly discuss the theoretical methods mentioned in previous works to estimate optimal futures hedge ratios. Interested readers can refer to the article written by Chen, Lee, and Shrestha (2003) for more detailed expositions.

Based on the objective function to be optimized, the theoretical methods can be divided into five categories: minimum variance hedge ratio, optimum mean-variance hedge ratio, Sharpe hedge ratio, mean-Gini coefficient based hedge ratio, and generalized semivariance based hedge ratio. And some of the above hedge ratios can be estimated by more than one method.

The minimum variance (MV) hedge ratio is one of the most prevailing hedging strategies (for example, Myers and Thompson, 1989). It is derived by minimizing the variance of the hedged portfolio. Suppose a portfolio containing one unit of a long spot position and h units of a short futures position. Let $\Delta S_t = S_{t+1} - S_t$ and $\Delta F_t = F_{t+1} - F_t$ be the changes in spot prices and the changes in futures prices, respectively. Since the fluctuations in spot positions can be reduced by holding positions in the futures contracts, the whole portfolio is called the hedged portfolio. The change in the value of the hedged portfolio is given by $\Delta H_t = \Delta S_t - h\Delta F_t$. The objective function concerned here is given below:

$$\min_h \operatorname{Var}(\Delta H) = \operatorname{Var}(\Delta S) + h^2 \operatorname{Var}(\Delta F) - 2h\operatorname{Cov}(\Delta S, \Delta F).$$

Then, the optimal hedge ratio $h = \dfrac{\operatorname{Cov}(\Delta S, \Delta F)}{\operatorname{Var}(\Delta F)}$ is derived by setting the first order condition of the objective function equal to zero. That is why the conventional approach to estimating the MV hedge ratio is to regress the changes in spot prices on the changes in futures price using the OLS technique. In order to take into consideration the feature of heteroscedastic in the error term of the above regression, the conditional second moments (i.e. variance and covariance) estimated from bivariate GARCH models are used to obtain time-varying hedge ratios. Investors can use this approach to update hedge ratios over time; hence, dynamic hedging strategies rather than a single hedge ratio for the entire hedging period is attainable. The random coefficient model suggested by Grammatikos and Saunders (1983) is another way that allows the hedge ratio to change over time, which in theory, can improve the effectiveness of the hedging strategy as well. Cointegration and error correction method is applied in the situation that spot price and futures price series could be non-stationary. The cointegration analysis is done by the following two steps. First, test if each series has a unit root (for example, Dickey and Fuller, 1981; Phillips and Perron, 1988). Then, if a single unit root is detected in both series, then implement cointegration test (for example, Engle and Granger, 1987). If the spot price and futures price series are verified to be cointegrated, then the hedge ratio needs to be estimated in two steps (for example, Ghosh, 1993; Chou, Fan, and Lee, 1996). The first step is to estimate cointegrating regression of the spot prices on the futures prices. The second step is to estimate the error correction model containing the residual series obtained from step one.

The method of optimum mean-variance hedge ratio blends the effects of both risk and return (for example, Cecchetti, Cumby, and Figlewski, 1988; Hsin, Kuo, and Lee, 1994). Assuming that the investor trades off return and risk in a linear fashion, the objective function is a linear combination of mean and variance of the hedged portfolio. Thus, the objective function is represented by the following form: $\max\ V(E(R_h),\sigma;A) = E(R_h) - 0.5A\sigma^2$, where R_h and σ^2 are the mean and variance of the hedged portfolio, respectively; A represents the risk aversion parameter. One potential problem inherent in this method is that the risk aversion parameter may vary with investors; hence, the optimal hedge ratio may depend on different individuals.

The method of Sharpe hedge ratio involves the maximization of the Sharpe ratio of the hedged portfolio (for instance, Howard and D'Antonio, 1984). According to Chen, Lee, and Shrestha (2003), when the expected value of risk-free interest rate is zero, the Sharpe hedge ratio degenerates to the MV hedge ratio estimated by the conventional approach.

Theoretically, the methods of mean-Gini (MEG) coefficient based hedge ratio and generalized semivariance (GSV) based hedge ratio hedge ratios are consistent with the second-order stochastic dominance principle. The mean extended-Gini coefficient based hedge ratio, however has no analytical solution and has to be estimated by numerically minimizing the mean extended-Gini coefficient, $\Gamma_\nu(R_h)$ defined as follows:

$\Gamma_{\nu}(R_h) = -\nu\,\mathrm{Cov}(R_h, (1 - G(R_h))^{\nu-1})$, where G is the cumulative probability distribution and ν is the risk aversion parameter. In practice, the theoretical covariance is replaced by the sample covariance, and the cumulative probability distribution function is estimated using the rank function:

$$\Gamma_{\nu}^{\text{sample}}(R_h) = -\frac{\nu}{N}\sum_{i=1}^{N}(R_{h,i} - \overline{R}_h)((1 - G(R_{h,i}))^{\nu-1} - \Theta),$$

where $\overline{R}_h = \frac{1}{N}\sum_{i=1}^{N} R_{h,i}$, $G(R_{h,i}) = \frac{\mathrm{Rank}(R_{h,i})}{N}$, and $\Theta = \frac{1}{N}\sum_{i=1}^{N}(1 - G(R_{h,i}))^{\nu-1}$.

Shalit (1995) has proved that as long as the futures and spot returns are jointly normally distributed, the minimum-MEG hedge ratio and the MV hedge ratio are the same.

Generalized semivariance based hedge ratio has no analytical solution either. The optimal hedge ratio is obtained by minimizing the GSV given as follows:

$V_{\delta,\alpha}(R_h) = \int_{-\infty}^{\delta}(\delta - R_h)^{\alpha}\,dG(R_h)$, where $G(R_h)$ is the probability distribution function of the return on the hedged portfolio R_h; δ represents the target return, and $\alpha > 0$ describes the attitude of risk aversion. Note that this method has a premise that the investors only regard the returns under the target return (δ) as risky. The optimal GSV based hedge ratio can be estimated by using its sample counterpart:

$V_{\delta,\alpha}^{\text{sample}}(R_h) = \frac{1}{N}\sum_{i=1}^{N}(\delta - R_{h,i})^{\alpha}\,U(\delta - R_{h,i})$, where $U(\delta - R_{h,i}) = 1$ if $\delta \geq R_{h,i}$; otherwise, $U(\delta - R_{h,i}) = 0$. Similar to the method of optimum mean-variance hedge ratio, no unique optimal hedge ratio is their common problem.

Even though the literature on estimating optimal hedge ratios has established a great many useful approaches, we concentrate on the MV-based approaches in this research. The following is our considerations. First, the MV hedge ratio is the most well-known and most widely-used hedge ratio. Second, all these methods mentioned above will converge to the same hedge ratio as the conventional MV hedge ratio if the futures price follows a pure martingale process and if the futures and spot prices are jointly normal. In order to investigate whether the dynamic hedging is more competent than the static hedging for risk reduction, we focus our attention on the comparison of the performance of the bivariate GARCH model with those of the conventional OLS method and the naïve hedge.

.4. Methodology

Initially, we compute the constant optimal hedge ratios as references. Comparisons of hedging performances between the conventional OLS method and the dynamic hedging strategy have been found in many previous studies (for example, Kroner and Sultan, 1993; Lien, Tse, and Tsui, 2000). The constant optimal hedge ratio $\mathrm{h} = \dfrac{\mathrm{Cov}(\Delta \mathrm{S}, \Delta \mathrm{F})}{\mathrm{Var}(\Delta \mathrm{F})}$ is derived by minimizing the variance of the hedged portfolio, containing spots and futures. Regressing ΔS_t on ΔF_t can capture this idea. To obtain the constant optimal hedge ratio, we estimate the coefficient (β) of the following regression:

$$\Delta S_t = \alpha + \beta \Delta F_t + e_t \qquad (1)$$

Then we move to estimate the dynamic hedge ratios. Bivariate GARCH models have proven useful in estimating time-varying hedge ratios in the literature (for example, Park and Switzer, 1995 and Lien, Tse, and Tsui, 2000, among many others). Baillie and Myers (1991) implemented bivariate GARCH models to estimate dynamic hedge ratios for six commodity futures. For each commodity, the optimal hedge ratio was computed as the estimated conditional covariance between cash and futures divided by the estimated conditional variance of futures. They claimed that the bivariate GARCH model fit their data well and that the dynamic hedging is more appropriate than the conventional OLS method. Kroner and Sultan (1993) proposed a bivariate GARCH error correction model to estimate the optimal hedge ratios for five currencies. Incorporating an error correction term into a bivariate GARCH model enabled them to consider the long-term cointegrating relationship between spot and futures. Their findings showed that the dynamic hedging strategy with error correction is more effective than the other two hedging strategies: the naïve hedge and the conventional hedge. They also noted that it may be important to incorporate an error correction term in currency markets while may not be necessary in other markets, such as commodity markets. Chen, Duan, and Hung (1999) proposed an extended bivariate GARCH model with maturity variables to depict the dynamics of the Nikkei-225 index and the futures-spot basis. By means of this setting, they investigated the Samuelson effect, which refers to a raise in volatility of futures prices around the expiration date, and compared the optimal hedge ratios with and without the maturity effect. They showed that the conditional variance of the futures price reduces as the contract approaches its maturity, which rejects the hypothesis of Samuelson effect. They also noted that the maturity of the futures is a crucial factor in determining the effectiveness of hedging.

In order to estimate the dynamic hedge ratios, and to investigate the leverage effect, we set up the bivariate GJR- GARCH model described as follows:

$$\Delta S_t = c_{11} + \sqrt{h_t}\,\varepsilon_t, \tag{2}$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_t^2 + \alpha_3 I_{t-1}\varepsilon_{t-1}^2, \tag{3}$$

$$\varepsilon_t \big| \mathcal{F}_{t\text{-}1} \sim N(0,1)$$

$$\Delta F_t = c_{22} + \sqrt{q_t}\,\omega_t, \tag{4}$$

$$q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \omega_t^2 + \beta_3 D_{t-1}\omega_{t-1}^2, \tag{5}$$

$$\omega_t \big| \mathcal{F}_{t\text{-}1} \sim N(0,1)$$

where Equation (2) and Equation (4) are the mean equations of the change in spot prices and the changes in futures prices, respectively; h_t and h_{t-1} are the current and lagged values of conditional variance of the change in spot prices; q_t and q_{t-1} are the current and lagged values of conditional variance of the change in futures prices. The dummy variable I_{t-1} in Equation (3) takes the value of one when ε_{t-1} is negative, otherwise it takes the value of zero, reflecting the asymmetry effects of bad and good news on the conditional volatility in the GJR-GARCH model. Similarly, the dummy variable D_{t-1} in Equation (5) takes the value of one when ω_{t-1} is negative, otherwise it takes the value of zero, reflecting the asymmetry effects of bad and good news on the conditional volatility. Following previous studies, the conditional correlation of two innovations is assumed constant in this model; thus we set $Cov_{t-1}(\varepsilon_t, \omega_t) = \rho$, independent of time. The dynamic hedge ratio is obtained by minimizing the conditional variance of the change in value of the hedged portfolio as follows:

$\min_{\eta_t} \; Var_{t-1}(\Delta H_t) = Var_{t-1}(\Delta S_t) + \eta_t^2 Var_{t-1}(\Delta F_t) - 2Cov_{t-1}(\Delta F_t, \Delta S_t)$. The first order condition of the objective function is

$\frac{\partial Var_{t-1}(\Delta H_t)}{\partial \eta_t} = 2\eta_t Var_{t-1}(\Delta F_t) - 2Cov_{t-1}(\Delta F_t, \Delta S_t)$. Setting this equal to zero, the dynamic hedge ratio is computed by $\eta_t = \frac{Cov_{t-1}(\Delta F_t, \Delta S_t)}{Var_{t-1}(\Delta F_t)}$, which can be rewritten as $\frac{\rho\sqrt{h_t q_t}}{q_t}$ in our notation. After estimating the bivariate GJR- GARCH model, we collect the estimated values of conditional correlation of two innovations, conditional variance of the change in spot prices, and conditional variance of the change in futures prices to compute the dynamic hedge ratios. An observation is worth mentioning here, namely, that the formula of dynamic hedge ratios is similar to that of constant hedge ratios, except that the former uses conditional variances and covariances, while the latter uses unconditional counterparts.

Following Kroner and Sultan (1993), we evaluate $Var(\Delta S_t - h_t \Delta F_t)$, the variance of the change in the value of the hedged portfolio, to compare hedging performance of different methods. h_t, the optimal hedge ratio, is set equal to unity, the constant optimal hedge ratios, and the time-varying dynamic hedge ratios for the naïve hedge method, the conventional OLS method, and the bivariate GJR-GARCH model, respectively.

5. Data and Empirical Results

The data used in this study are obtained from the LIFFE database. LIFFE is chosen because it has SSFs traded on over one hundred individual stocks in England, the United States, and Europe. More than 80% of the SSFs listed on the LIFFE are traded on securities outside England, and these SSFs are so-called “foreign-listed” for their domestic stock markets. The SSFs listed on the LIFFE are also called universal stock futures (USFs). For credibility reasons, the data initially included the top ten active SSFs listed on the LIFFE. However, among these SSFs, the underlying stock of the second one (i.e. Vodafone Group plc) is listed on the London Stock Exchange. Hence, based on our criterion of foreign listing, the data of that SSF is omitted from the analyses. The data was collected until April 19, 2002 but each SSF may have different data periods depending on their introduction dates. The average number of observations is about 280. Table 2 lists the dates of introduction of the remaining nine SSF contracts.

TABLE 2 ABOUT HERE

Table 3 displays the estimated constant optimal hedge ratios for the nine groups of data. Constant optimal hedge ratios are above 90%, except for the three SSFs (Eni SpA, Enel SpA, and UniCredito Italiano SpA) whose underlying stocks are traded in Italy.

TABLE 3 ABOUT HERE

As shown in Table 4, the coefficient (α_3) on the dummy variable I_{t-1} in Equation (3) and the coefficient (β_3) on the dummy variable D_{t-1} in Equation (5) are both significantly positive in Telecom Italia SpA and Royal Dutch Petroleum Co, reflecting that bad shocks, indeed, impact conditional volatility more than good news in the two groups of data. The leverage effect can also be found in the data series of

Telecom Italia Mobile SpA's futures and that of UniCredito Italiano SpA's futures.

TABLE 4 ABOUT HERE

The constant correlation (ρ) is significantly positive for all nine groups of data. Except for Eni SpA, Enel SpA, and UniCredito Italiano SpA, ρ is over 90%. Comparing Table 3 and Table 4, we find that there seems to be a positive relationship between constant optimal hedge ratios in Equation (1) and the constant correlation in the bivariate GJR- GARCH model. The significance of the other coefficients for the explanatory variables depends on the security.

Figure 1 plots the dynamic hedge ratios and conventional constant hedge ratios. After applying the augmented Dicky-Filler test (ADF) to check if the series of dynamic hedge ratios have a unit root, we find that except for those of Enel SpA and Nokia OYJ, the series of dynamic hedge ratios have no unit root at the 5% level. In addition, we find by visual examination that the conventional OLS method tends to under-hedge for the series of Eni SpA and Enel SpA.

INSERT FIGURE 1 ABOUT HERE

The comparisons of hedging performance of various approaches are illustrated in Table 5. Based on minimum hedged portfolio variances, the performance of dynamic hedging is the best of the three methods and that of naïve hedge is the worst, excluding the data series of Banco Bilbao Vizcaya Argentaria SA and UniCredito Italiano SpA.

TABLE 5 ABOUT HERE

6. Conclusions

In this paper, we used data obtained from the London International Financial Future and Options Exchange (LIFFE) database to estimate the dynamic hedge ratios of foreign-listed SSFs and to compare the hedging performance of this method and those of the naïve hedge as well as the conventional OLS method. The estimated results of the GJR-GARCH model suggest that bad shocks may impact conditional volatility more than good news in our researched data, reflecting leverage effect reported in many studies.

The results show that the three SSFs- Eni SpA, Enel SpA, and UniCredito Italiano SpA- with their underlying stocks traded in Italy have both lower constant optimal hedge ratios and lower constant correlation in the bivariate GJR- GARCH model. This indicates that the relationship between the SSFs market and their domestic underlying market in Italy is less close. Since Italy is relatively farther from England, it seems that the tightness of relation between foreign listed derivatives and their domestic underlying markets varies with distance. Besides, we find that the series of dynamic hedge ratios display stationary, except for those of Enel SpA and Nokia OYJ with underlying stocks traded in Finland. The result implies that while the impact of shocks to hedge ratios of foreign listed SSFs with underlying stocks traded closer to England eventually decays, which is similar to the findings of currency markets mentioned by Kroner and Sultan (1993), the dynamic hedge ratios of foreign listed SSFs with underlying stocks traded farther from England behave as random walks, which is similar to the findings of commodity markets reported by Baillie and Myers (1991). It appears that the two findings listed above offer sufficient evidence supporting the hypothesis that locations or distance do matter in analyzing trading activities.

Since the constant optimal hedge ratios are over 90% for most series, the differences between the effectiveness of risk reduction of the naïve hedge and that of the conventional OLS method are trivial. Nevertheless, our findings suggest that in general, the hedging performance of dynamic hedging is the best of the three methods, the performance of the conventional OLS method is the second best, and the naïve hedge is the worst. One possible explanation is that the dynamic hedging method gives more flexibility for the users to fine tune the hedge ratios when the market situation fluctuates, while the naïve hedging ratio and the conventional constant hedging ratio remain rigid regardless of market fluctuations.

We acknowledge that our research still has some limitations that should be kept in mind and need to be improved in future studies. As shown in Table 5, even though the dynamic hedging performs better than the other methods in our study, the outperformances are not significant. While several studies note that even taking transaction cost into consideration, dynamic hedging offers better a hedging strategy (e.g., Kroner and Sultan, 1993; Park and Switzer, 1995), other studies mention computational costs which may diminish the effectiveness of dynamic hedging (e.g., Lien, Tse, and Tsui, 2000). Thus future research should be done in the presence of transaction costs and other costs such as computational costs and reexamination costs to investigate whether dynamic hedging could maintain its leading position among hedging strategies.

We have compared the hedging performances of three methods in our research. In addition to naïve hedge, conventional OLS method, and dynamic hedging, other methods such as generalized semivariance (GSV) or mean extended-Gini (MEG) may prove to be noteworthy as well. We plan to remedy this omission in future work by applying numerical methods to estimate the hedge ratios of GSV or MEG.

Horizon effect is another interesting topic worth exploring. However, this kind of research requires much longer sample periods. Unfortunately, since the SSFs are a newly developed type of derivative, we do not have enough samples to implement this kind of research. Hence, we suggest that questions such as whether the optimal hedge ratio approaches the naïve hedge ratio when the hedging horizon becomes longer can be investigated in a future study.

Finally, we merely focused our interest on the SSFs listed on the LIFFE in the United Kingdom. Since SSFs have already traded on several exchanges, including those in the United States, Spain, Portugal, Australia, and so on, future work could potentially incorporate data from other exchanges to expand the scope of this research.

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Table 1

Contract Specifications

Country	Exchanges	Number of SSFs listed	Contract unit	Delivery months	Settlement	Daily Price Limits
The United Kingdom	London International Financial Future and Options Exchange (LIFFE) www.liffe.com	116	100 shares of the underlying stock in Europe (except for Italy and England), or 1000 shares of the underlying stock in Italy, the United States, and England.	two consecutive months and two near quarter months	cash	none
The United States	NQLX www.nqlx.com	99	100 shares of the underlying stock	two near term serial months and two quarterly months	physical delivery	none
	OneChicago www.onechicago.com	92				

Table 1 (Continued)

Contract Specifications

Country	Exchanges	Number of SSFs listed	Contract unit	Delivery months	Settlement	Daily Price Limits
Australia	Sydney Futures Exchange (SFE) www.sfe.com.au	40	200 shares of Ansell stock, or 1000 shares of other underlying stock	up to 12 months ahead for Telstra Corporation ISFs, or four quarterly months for others	cash for Telstra Corporation ISFs, or physical delivery for others	minimum price movement of contract size multiplied by 1 cent of A$
Spain	MEFF www.meff.com	9	100 shares of the underlying stock	four quarterly months, or other months if needed	holder-chosen between cash and psychical delivery	minimum price fluctuation of contract unit multiplied by 1 cent of EURO

Table 1 (Continued)

Contract Specifications

Country	Exchanges	Number of SSFs listed	Contract unit	Delivery months	Settlement	Daily Price Limits
Portugal	Euronext Lisbon www.euronext.pt	7	100 shares of the underlying stock	the current month, the following calendar month and the two closest quarterly months	physical delivery	not available

Table 2

The Dates of Introduction for the Nine SSF Contracts

Name (Symbol)	Country	Listing exchange	Introduction date	Data period	Observations
Eni SpA (ENI)	Italy	Borsa Italiana[a]	2001/01/29	2001/01/29-2002/4/19	303
Telecom Italia SpA (TI)	Italy	Borsa Italiana	2001/01/29	2001/01/29-2002/4/19	303
Banco Bilbao Vizcaya Argentaria SA (BVA)	Spain	Bolsa De Madrid[b]	2001/05/14	2001/05/14-2002/4/19	229
Telecom Italia Mobile SpA (TIM)	Italy	Borsa Italiana	2001/03/19	2001/03/19-2002/4/19	268
Nokia OYJ (NOK)	Finland	Helsinki Exchange[c]	2001/01/29	2001/01/29-2002/4/19	297
Enel SpA (ENL)	Italy	Borsa Italiana[d]	2001/03/19	2001/03/19-2002/4/19	268
UniCredito Italiano SpA (UC)	Italy	Borsa Italiana	2001/03/19	2001/03/19-2002/4/19	268
Telefonica SA (TEF)	Spain	Bolsa De Madrid[e]	2001/01/29	2001/01/29-2002/4/19	299
Royal Dutch Petroleum Co (RD)	Netherlands	Euronext Amsterdam[f]	2001/01/29	2001/01/29-2002/4/19	304

[a] ENI is also listed on the New York Stock Exchange (NYSE).

[b] BVA is also listed on the NYSE.

[c] NOK is also listed on the NYSE and the Stockholm Stock Exchange.

[d] ENL is also listed on the NYSE.

[e] TEF is also listed on the NYSE, the Buenos Aires Stock Exchange, the Lima Stock Exchange, the Sao Paulo Stock Exchange, the London Stock Exchange, the Paris Stock Exchange, the Frankfurt Stock Exchange, and the Tokyo Stock Exchange.

[f] RD is also listed on the NYSE.

Table 3

Constant Optimal Hedge Ratios

Name (Symbol)	Eni SpA (ENI)	Telecom Italia SpA (TI)	Banco Bilbao Vizcaya Argentaria SA (BVA)	Telecom Italia Mobile SpA (TIM)	Nokia OYJ (NOK)	Enel SpA (ENL)	UniCredito Italiano SpA (UC)	Telefonica SA (TEF)	Royal Dutch Petroleum C0 (RD)
Hedge ratio	0.151168	0.915792	0.96013	0.902621	0.971574	0.191883	0.424539	0.942677	0.989487

Table 4

Estimates from the Following Bivariate GARCH Model:

$$\Delta S_t = c_{11} + \sqrt{h_t}\varepsilon_t,\ h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_t^2 + \alpha_3 I_{t-1}\varepsilon_{t-1}^2,\ \varepsilon_t \big| \mathcal{F}_{t-1} \sim N(0,1)$$

$$\Delta F_t = c_{22} + \sqrt{q_t}\omega_t,\ q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \omega_t^2 + \beta_3 D_{t-1}\omega_{t-1}^2,\ \omega_t \big| \mathcal{F}_{t-1} \sim N(0,1)$$

$$Cov_{t-1}(\varepsilon_t, \omega_t) = \rho$$

Name (Symbol)	Eni SpA (ENI)	Telecom Italia SpA (TI)	Banco Bilbao Vizcaya Argentaria SA (BVA)	Telecom Italia Mobile SpA (TIM)	Nokia OYJ (NOK)	Enel SpA (ENL)	UniCredito Italiano SpA (UC)	Telefonica SA (TEF)	Royal Dutch Petroleum Co (RD)
Estimated values									
Stock dynamic									
c_{11}	0.006503	-0.024387*	-0.015124	-0.007717	-0.050458	0.000475	0.004131	-0.024098	-0.037102
	(0.69433)	(0.02306)	(0.48055)	(0.38662)	(0.39553)	(0.93545)	(0.29699)	(0.24341)	(0.5367)
α_0	0.157214*	0.020572*	0.010834	0.017907	0.001394	0.000457	0.000344	0.039372	0.072089*
	(0.00000)	(0.00003)	(0.14047)	(0.16168)	(0.76311)	(0.24999)	(0.13199)	(0.18983)	(0.02208)
α_1	-0.990224*	0.376154*	0.81116*	0.014178	0.981176*	0.925811*	0.825975*	0.621068*	0.872009*
	(0.00000)	(0.00129)	(0.00000)	(0.98412)	(0.00000)	(0.00000)	(0.00000)	(0.0181)	(0.00000)
α_2	0.06268*	-0.056872	0.079961	-0.035977	0.01428	0.057858	0.089084	0.083769	-0.007455
	(0.01235)	(0.16368)	(0.21652)	(0.53800)	(0.12962)	(0.1356)	(0.07339)	(0.16144)	(0.79886)
α_3	-0.021635	0.423939*	-0.011796	0.082984	-0.001392	-0.041358	-0.017772	-0.025814	0.128089*
	(0.23054)	(0.00011)	(0.85583)	(0.25992)	(0.89612)	(0.33818)	(0.776)	(0.64826)	(0.00782)

Table 4 (Continued)

Estimates from the Following Bivariate GARCH Model:

$$\Delta S_t = c_{11} + \sqrt{h_t}\varepsilon_t,\ h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_t^2 + \alpha_3 I_{t-1}\varepsilon_{t-1}^2,\ \varepsilon_t | \mathcal{F}_{t-1} \sim N(0,1)$$

$$\Delta F_t = c_{22} + \sqrt{q_t}\omega_t,\ q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \omega_t^2 + \beta_3 D_{t-1}\omega_{t-1}^2,\ \omega_t | \mathcal{F}_{t-1} \sim N(0,1)$$

$$Cov_{t-1}(\varepsilon_t, \omega_t) = \rho$$

SSF dynamic									
c_{22}	-0.00576	-0.025359*	-0.01503	-0.006709	-0.054293	0.002439	0.000425	-0.029413	-0.03595
	(0.712379)	(0.01922)	(0.48046)	(0.46967)	(0.36808)	(0.7181)	(0.93718)	(0.16152)	(0.55913)
β_0	-0.00013	0.016355*	0.011598	0.027513*	-0.000095	-0.000082*	0.000444*	0.04029	0.059263
	(0.695165)	(0.00000)	(0.13102)	(0.00000)	(0.98024)	(0.00733)	(0.01195)	(0.06455)	(0.05418)
β_1	1.014871*	0.4795*	0.777268*	-0.439048*	0.984757*	1.010187*	0.89373*	0.616446*	0.904706*
	(0.00000)	(0.00000)	(0.00000)	(0.03421)	(0.00000)	(0.00000)	(0.00000)	(0.00056)	(0.00000)
β_2	-0.015337*	-0.057138	0.125033	-0.020696	0.006028	-0.007617*	-0.02635	0.138481*	-0.009304
	(0.00000)	(0.07635)	(0.13928)	(0.6061)	(0.51144)	(0.00000)	(0.233812)	(0.01448)	(0.67291)
β_3	0.01146	0.483575*	-0.054571	0.099128*	0.010291	0.000426	0.165203*	-0.107358	0.090732*
	(0.09965)	(0.00000)	(0.4463)	(0.03373)	(0.39604)	(0.89806)	(0.001438)	(0.11076)	(0.00822)
Constant	0.711278*	0.956246*	0.947445*	0.938606*	0.974073*	0.775616*	0.626297*	0.965296*	0.971971*
correlation ρ	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	300	302	228	267	296	267	267	298	303

1. Figures in parentheses are p-values. 2. An asterisk marks statistical significance at the 5% level.

Table 5

Comparisons of Hedging Performance by Variances

$$Var(\Delta S_t - h_t \Delta F_t)$$

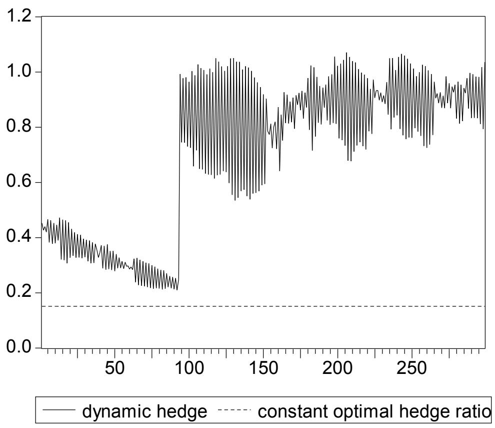
Name (Symbol)	Eni SpA (ENI)	Telecom Italia SpA (TI)	Banco Bilbao Vizcaya Argentaria SA (BVA)	Telecom Italia Mobile SpA (TIM)	Nokia OYJ (NOK)	Enel SpA (ENL)	UniCredito Italiano SpA (UC)	Telefonica SA (TEF)	Royal Dutch Petroleum Co (RD)
Portfolio variance									
Naïve hedge (h_t=1)	0.21838	0.00430	0.00980	0.00239	0.06834	0.05334	0.00534	0.00940	0.05847
Conventional hedge ($h_t = \beta$)	0.06907	0.00400	0.00965	0.00220	0.06736	0.01155	0.00221	0.00896	0.05836
Dynamic hedge ($h_t = \eta_t$)	0.04770	0.00378	0.00984	0.00219	0.06603	0.00643	0.00223	0.00880	0.05677

Figure 1

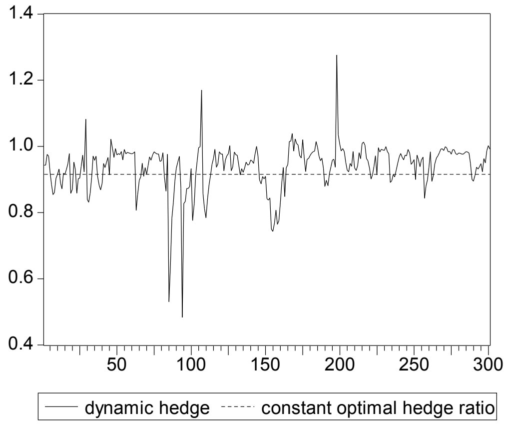
The optimal hedge ratio over the sample periods under two assumptions:

time-varying volatility, and constant volatility

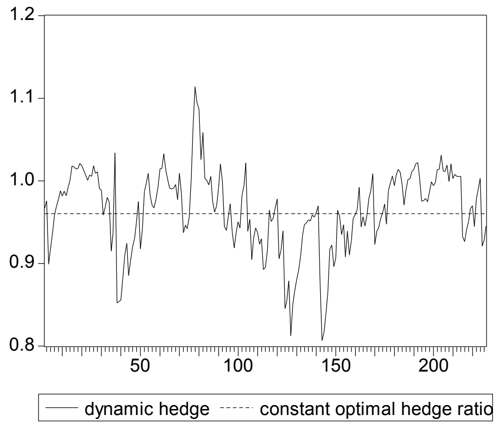
ENI



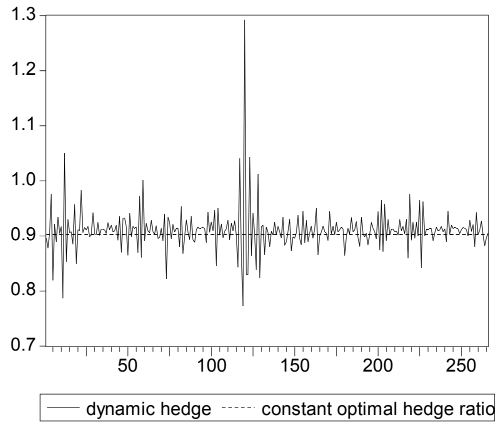
TI



BVA



TIM



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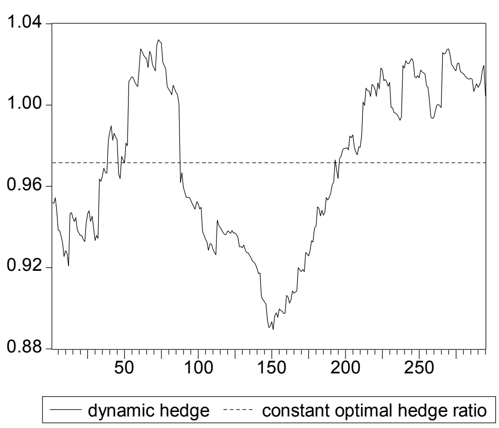


ENL

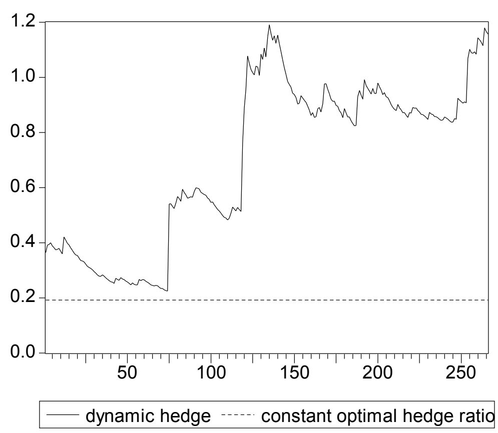
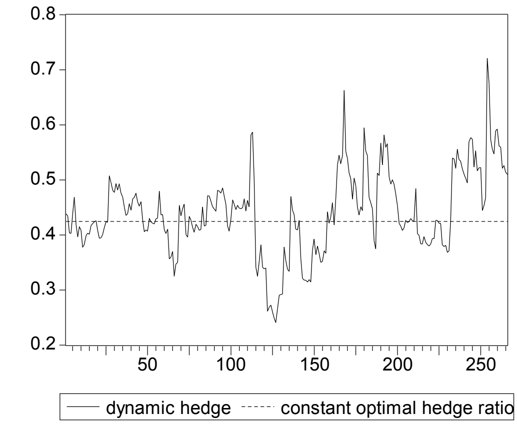


Figure 1 (Continued)

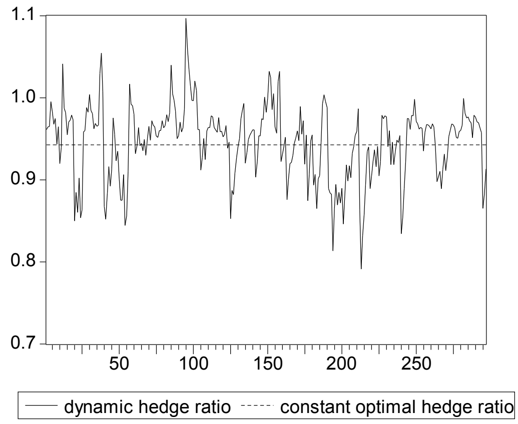
The optimal hedge ratio over the sample periods under two assumptions:

time-varying volatility, and constant volatility

UC



TEF



RD