THE HEDGING EFFECTIVENESS OF CURRENCY FUTURES

by

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ABSTRACT

This project compares four different hedging techniques using spot and futures exchange rates of the British Pound. Specifically, the OLS regression model, the vector autoregressive model (VAR), the vector error correction model (VECM) and the Multivariate GARCH with error correction model are applied. Hedging effectiveness is measured in terms of minimizing variance of hedged portfolios. The VAR model and the VECM offer the same performance, which is higher than that of the OLS model. Although the multivariate GARCH with error correction model is the only one being able to capture the time varying nature of the hedge ratio, the hedging performances of four strategies do not differ very much, either in-sample or out-of-sample. Therefore, although complex models are able to capture more figures of the data set, there is no evidence that they will give significant better hedging performance.

Keywords: hedge ratio, hedging effectiveness, currency futures
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AUTHORS’ CONTRIBUTIONS

Zongye Chen collects data and analyzes the results.

Tingting Ye analyzes results and drafts the manuscript.
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1 INTRODUCTION

Hedgers use derivative securities to reduce the risk from variations in the spot market. They usually short an amount of futures contracts if they hold the long position on the underlying assets, and vice versa. An important question is how many futures contracts are needed. In other words, investors have to decide on the optimal hedge ratio, that is how many futures contracts should be held for each unit of the underlying assets. The hedge ratio is defined by Hull (2003, p.750) as “the ratio of the size of the portfolio taken in futures contracts to the size of the exposure”.

The appropriate way to calculate hedge ratios remains a controversial issue in the literature. According to Lien and Luo (1993), there are four major methodologies for hedging with futures contracts. These methodologies are: 1) the ordinary least squares (OLS); 2) the vector autoregression (VAR); 3) a Vector Error Correction Model (VECM); 4) the Multivariate GARCH with error correction model. In this project, we use these four methodologies to calculate hedge ratios, and add a simple naïve hedge method in Section 4 to compare hedging effectiveness.

According to Ederington (1979), the OLS model is the earliest and simplest method to estimate a hedge ratio of the change in spot prices on the change in futures price. However the OLS model does not take into account serial correlation. This problem can be overcome using a VAR. But the VAR model does not test the cointegration relationship between the spot and futures prices. This is an important problem. Lien (1996, p.776) points out that “a hedger who omits the cointegration relationship will adopt a smaller than optimal futures position, which results in a relatively poor hedging performance”. Study by Kroner and Sultan (1993) shows that
if the spot and futures currency prices are cointegrated, there must be an error correction representation that includes both the short term dynamics and long term information. Therefore we incorporate the cointegrating vector in the VAR to obtain a Vector Error Correction Model (VECM). All three models previously discussed have the problem of implicitly assuming that the minimum risk hedge ratio is constant through time. However, this assumption is untrue in reality. New information usually has a big influence on the changes in the risk of the various assets and the risk minimizing hedge ratios should be time varying. Hence we use the Multivariate GARCH model which has already been applied in Thomas and Brooks (2001) to solve this problem.

Then we add the naïve hedge which assumes a unitary hedge ratio for comparison. We evaluate and compare the hedging effectiveness of four hedging techniques discussed previously and the naïve one. Our results are consistent with that of Thomas and Brooks (2001) showing that there is no significant difference in hedging effectiveness between GARCH and OLS hedge ratio estimates.

The remainder of this project is organized as follows. Section 2 reviews theories and background related to the analysis. Section 3 illustrates the data characteristics and sources and describes the research methodology which includes the background of all four models. Section 4 presents the estimation results of the statistical models and estimated hedge ratios. The hedging performance comparison is provided in Section 5, and Section 6 concludes the project.
2 REVIEW OF HEDGING THEORIES

2.1 Theories about hedge ratio

Johnson (1960) and Stein (1961) first apply the mean variance framework of Markowitz (1952) to futures hedging. After that, Ederington (1979) develops the theory into the well-known OLS-based method which relates changes in cash prices ($\Delta S$) to changes in futures prices ($\Delta F$). He states that the minimum variance hedge ratio is the ratio of the covariance between the futures and spot price to the variance of the futures price. Because the purpose of hedging is to minimize the variance of the asset portfolio, the minimum variance hedge ratio should be the optimal hedge ratio:

$$h^*_{t-1} = \frac{\sigma_{S,F,t}}{\sigma^2_{F,t}}$$

where $\sigma^2_{F,t}$ is the variance of the futures contract and $\sigma_{S,F,t}$ is the covariance of the futures and the spot position on the underlying assets. $h$ is negative, because the hedging of a long position requires a short position in the corresponding futures contract and vice versa.

In fact, many studies are developed on the optimal hedge ratio with various similar techniques. Two assumptions are commonly made. The first one is that the spot and futures prices changes are not cointegrated which means that both the spot and futures prices follow random walks and they will not move together in the long run. The second assumption is that the conditional variance-covariance matrix of the hedged portfolio is constant through time meaning there is no heteroskedasticity. If both assumptions are satisfied, Malliaris and Urrutia (1991) and
Benet (1992) prove that a constant optimal hedge ratio can be obtained from the slope coefficient $h$ in the regression: $\Delta S_t = \alpha + h \Delta F_t + \varepsilon_t$.

However, what follow immediately are criticisms mainly in respect of the inefficiency of the ordinary least square regression methodology. An example of this is serial correlation between spot and futures prices as suggested by Herbst et al. (1989) and heteroskedasticity as mentioned by Park and Bera (1987). These two problems are ignored by the OLS method when calculating the minimum variance hedge ratio.

It is necessary to establish a new model that includes the time-varying figure of the covariance to overcome the above two problems of the OLS method. In order to allow for time variation in the covariance matrix of $\Delta S$ and $\Delta F$, Baillie and Myers (1991), Myers (1991), and Park and Switzer (1995) propose the use of hedging strategies based on the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model.

Thomas and Brooks (2001) use constant correlation multivariate GARCH and threshold ARCH specifications to estimate and to compare time-varying hedge ratios from the Australian All Ordinaries Index (AOI) and the corresponding Share Price Index (SPI). However in financial markets, it is not realistic to assume that constant correlation hypothesis will hold for all financial time series. For example Bera and Roh (1991) test the constant correlation hypothesis for many financial time series, and in most cases, the null hypothesis of constant correlation is rejected.

Therefore, the following study extends the study of Thomas and Brooks (2001) to consider an alternative model more suited to conditional hedging: a Multivariate Vector Error Correction GARCH model that allows for time-varying conditional correlation (Bollerslev et al., 1988). The Multivariate Vector Error Correction GARCH model we use here is an extension of the Univariate Vector Error Correction GARCH model. The Multivariate Vector Error Correction GARCH
model is used efficiently in calculating dynamic time-varying hedge ratios, conditioned on the information available at the beginning of the period.

2.2 Theories about hedging effectiveness

This study also contributes to the existing published literature on hedging effectiveness. With time-varying hedge ratios, we study whether dynamic hedge ratios calculated from a more complicated GARCH framework outperform constant counterparts in hedging effectiveness.

Many studies compare the hedging effectiveness of hedge ratios calculated from different models. Baillie and Myers (1991) and Myers (1991), using US commodity and financial futures to examine hedging effectiveness of the constant hedge approach by following a dynamic strategy, find that time-varying hedge ratios outperform constant hedge ratios. Myers (1991) is not the only one who concludes that it may be simple and accurate to use the constant optimal hedge ratios and use linear regression approaches. Kroner and Sultan (1993) also prove that constant hedge ratio method is simple and accurate using five currency futures over the period 1985-1990. Chakraborty and Barkoulas (1999), using futures contracts on five leading currencies to test the GARCH (1, 1) covariance structure model, show that only in one of five cases, the time-varying optimal hedge ratio outperforms the constant hedge ratio. More recently, Thomas and Brooks (2001) also do not find a significant difference in hedging effectiveness between GARCH and OLS hedge ratio estimates.

Lien and Tse (1999) use a fractionally integrated error correction model to estimate the hedge ratio and they compare the results of this model with these of other models: OLS, VAR, EC and ARFIMA-GARCH. They use daily data of the Nikkei Stock Average Index starting in 1989 and ending in 1996. They find that VAR, EC, ARFIMA-GARCH and fractionally integrated error correction models outperform the OLS estimation of the minimum variance hedge ratio.
However, Moosa (2003) addresses the problem that different hedge ratio estimating methods can strongly affect the effectiveness of hedging. He compares four models: a level model, a first difference model, a simple error correction and a general error correction model by using two different sets of data. The first data is a group of monthly observations on cash and futures prices of Australian stocks and the second data is a group of quarterly observations covering the period 1987 – 2000 on the spot exchange rates of the pound and the Canadian dollar against the US dollar. He finds that there is no significant difference for hedging effectiveness in both cases no matter what models they use. For this reason Moosa (2003, p.19) concludes that “Although the theoretical arguments for why model specification does matter are elegant, what really matters for the success or failure of a hedge is the correlation between the prices of the unhedged position and the hedging instrument”.

2.3 Summary of literature review

Many researchers have proposed the estimation of time-varying optimal hedge ratios using GARCH models and GARCH extensions (Baillie & Myers, 1991; Myers, 1991; Kroner & Sultan, 1993; Park & Switzer, 1995; Brooks, 2002). Moreover, many researchers also agree that if the presence of cointegration exists, we should apply the error correction term (Lien, 1993; Kroner & Sultan, 1993). More complicated extensions of GARCH model have also been offered in recent years (Lien & Tse, 1999; Brooks, 2002).

However, some authors argue that more complex models have considerable disadvantages although they are expected to give a better performance. Firstly, some of these methods are too difficult to estimate (Lien, 2002). Secondly, there is no significant hedging performance difference between simple methods like the OLS and complex models like GARCH. Indeed, models like OLS can get similar levels of performance many times (Myers, 1991; Miffre, 2001).
In conclusion, although complex models are able to capture more features of the data set, there is no evidence that they will give significant better hedging performance.
3 RESEARCH METHOD

3.1 Data description

The data used in this study is spot and futures exchange rates of the British Pound. The spot exchange rate is obtained from Bank of England\(^1\), while the futures exchange rate is downloaded from the Chicago Mercantile Exchange\(^2\) (CME). The date starts on July 18, 1994 and ends on March 1, 2006, resulting in 2908 observations (after removing non-trading days). We only use the first 2,878 observations in the test and leave the last 30 observations for an out-of-sample hedge ratio performance comparison.

There are four delivery months per annum for the currency futures contracts: March, June, September and December. In our empirical test, we roll over a contract, for example, September contract, on its delivery date, September 30, and compute the price change from the prices on September 29 and September 30. To compute the price change for October 1, we use prices on September 30 and October 1 from the next contract, the December contract.

We calculate the return series for the cash portfolio and futures contract as the logarithmic price change:

\[
\Delta S_t = R_{S,t} = \log \left( \frac{P_{S,t}}{P_{S,t-1}} \right) \\
\Delta F_t = R_{F,t} = \log \left( \frac{P_{F,t}}{P_{F,t-1}} \right)
\]

\(^1\) http://213.225.136.206/mfsd/iadb/Rates.asp?Travel=Nlx&into=GBP&latest=
\(^2\) http://www.cme.com/trading/dta/hist/daily_settle_prices.html?type=cur
where \( \Delta S_t \) and \( \Delta F_t \) are the daily returns on the cash and futures positions and \( P_s \) and \( P_f \) are the spot and futures prices. Furthermore, \( R_{s,t} \) and \( R_{f,t} \) are assumed to be normally distributed.

### 3.2 Models

Four models are used to estimate the optimal hedge ratio of currency: the OLS, the VAR, the VECM, and the multivariate GARCH with error correction model.

#### 3.2.1 The Ordinary Linear Regression Model (OLS)

OLS is the earliest and simplest model to estimate a hedge ratio of the change in spot prices on the change in futures price. This method has been widely applied in the literature.

The linear regression is used as follows:

\[
\Delta S_t = \alpha + \beta \Delta F_t + \epsilon_t
\]

where \( \Delta S_t \) and \( \Delta F_t \) are defined in equation (1) and equation (2), \( \alpha \) is the constant term and \( \epsilon_t \) is the error term from the OLS model, while the slope \( \beta \) is the estimate for the minimum variance hedge ratio \( h^* \).

In order to examine whether there is serial correlation between the error terms, we apply a Durbin-Watson test. Because most regressions of time series data have the problem of positive autocorrelation, the hypotheses in the Durbin-Watson test are

\[
H_0: \rho = 0
\]

\[
H_1: \rho > 0
\]

---

The test statistic is:

\[ d = \frac{\sum_{i=2}^{n} (e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2}. \]

If \( d < d_L \), reject \( H_0: \rho = 0 \),

if \( d > d_U \), do not reject \( H_0: \rho = 0 \),

if \( d_L < d < d_U \), test is inconclusive.

The Bera-Jarque test is also applied to examine whether distributions are normal. The Bera-Jarque test is the most commonly used technique and it is based on the skewness and kurtosis of a distribution.

### 3.2.2 The Vector Autoregressive Model (VAR)

As we discussed previously, the OLS model does not take into account the serial correlation. This problem can be overcome in a VAR model. In the VAR model, there are two variables in a regression, while the current value depends on the previous value of both variables. The model has already been tested by Yang (2001) for the Australian market and it can be described with the following two equations:

\[
\Delta S_i = \alpha_s + \sum_{i=1}^{k} \beta_{si} \Delta S_{t-i} + \sum_{i=1}^{k} \lambda_{si} \Delta F_{t-i} + \varepsilon_{si} \tag{3}
\]

\[
\Delta F_i = \alpha_f + \sum_{i=1}^{k} \beta_{fi} \Delta S_{t-i} + \sum_{i=1}^{k} \lambda_{fi} \Delta F_{t-i} + \varepsilon_{fi} \tag{4}
\]
where $\alpha$ is the constant term and $\varepsilon_\mu$ and $\varepsilon_\beta$ are independently identically distributed (iid) error terms, and the optimal lag $k$ is the total number of parameters estimated\(^4\).

Deciding on the appropriate model orders from autocorrelation functions is difficult in practice. An easier way is to choose the model that minimizes the value of an information criterion.

An ARMA (p, q) test is conducted in order to calculate $k$, where $k=p+q-1$. $k$ is determined by finding the minimum AIC and BIC, while AIC and BIC are defined as:

\[
\text{AIC} = \ln(\hat{\sigma}^2) + \frac{2k}{T} \\
\text{BIC} = \ln(\hat{\sigma}^2) + \frac{k \ln T}{T}
\]

where $\hat{\sigma}^2$ is the estimator of the variance of residual value estimated in the ARMA (p, q) test. $k$ is the number of parameters and $T$ is the sample size. When using the criterion based on the estimated standard errors, the model with the lowest value of AIC and BIC should be chosen.

Let $\sigma^2 (\varepsilon_\beta) = \sigma_{\beta\beta}$, and $\text{cov}(\varepsilon_\mu, \varepsilon_\beta) = \sigma_{\mu\beta}$, the optimal hedge ratio from the model is defined as follows:

\[
h^* = \frac{\sigma_{\mu\beta}}{\sigma_{\beta\beta}}
\]

\(^4\) $k$ is defined by the multivariate versions of the Akaike’s and Schwarz’s Bayesian information criteria.
3.2.3 The Vector Error Correction Model

The VAR model does not test the cointegration relationship between the variables. This is an important problem, because if the spot and futures currency prices cointegrated which will ignore the error correction, the regression will be misspecified (Kroner & Sultan, 1993). Furthermore it may produce an inaccurate hedge ratio. Therefore, cointegration must be tested before we perform any further test.

We test whether the residuals $e_t$ are stationary. If $S_t$ and $F_t$ are not co-integrated, any linear combination of them will be nonstationary, and hence the residuals will be nonstationary. Specifically, we test the hypothesis that $e_t$ is not stationary, i.e., the hypothesis of no co-integration.

A test of the hypothesis that $e_t$ is nonstationary can be done in two ways. One way is to conduct a Dickey-Fuller test on the residual series, and the other way is to conduct a Durbin-Watson test. Here we simply use the Durbin-Watson statistic from the co-integrating regression.

$$DW = \frac{\sum(e_t - e_{t-1})^2}{\sum(e_t)^2}$$

If $e_t$ follows a random walk, the expected value of $(e_t, e_{t-1})$ will be zero, and so the Durbin-Watson statistic should be close to zero. Thus, we can simply test the null hypothesis that $DW=0$. Therefore if the DW value is greater than the critical value, we reject the hypothesis that $DW=0$, in other words, $S_t$ and $F_t$ are co-integrated. If the DW value is smaller than the critical value, we cannot reject the hypothesis that $DW=0$, in other words, $S_t$ and $F_t$ are not cointegrated.
Once we find that $S_t$ and $F_t$ are cointegrated, we must incorporate the cointegrating vector in the VAR to obtain a Vector Error Correction Model. Then VECM can be written as follows:

$$\Delta S_t = c_s + \sum_{i=1}^{k} \beta_s \Delta S_{t-i} + \sum_{i=1}^{k} \lambda_s \Delta F_{t-i} - \alpha_s E_{t-1} + \varepsilon_s$$

$$\Delta F_t = c_f + \sum_{i=1}^{k} \beta_f \Delta S_{t-i} + \sum_{i=1}^{k} \lambda_f \Delta F_{t-i} + \alpha_f E_{t-1} + \varepsilon_f$$

where $\varepsilon$ is the error correction term, $c_s$ and $c_f$ are the intercepts and $\alpha_s$ and $\alpha_f$ are the coefficients of error correction term to measure at what speed each market responds to the deviation from the long term stability relationship.

We can still use equation (7) to calculate the constant hedge ratio.

3.2.4 The Multivariate GARCH with error correction model

All the models previously discussed have the problem of implicitly assuming that the minimum risk hedge ratio is constant through time irrespective of whether the hedge is undertaken or not. However, this assumption is untrue in reality. New information usually has a big influence on the changes in the risk of the various assets. So the risk minimizing hedge ratios should be time varying. Therefore in order to produce proper risk-minimizing hedge ratios, risk reduction properties should be considered.

Vector Error Correction which represents the conditional mean equation is given as follows:

$$\Delta S_t = c_0 + \gamma_0 E_{t-1} + \varepsilon_s$$
\[ \Delta F_t = c_1 + \gamma_1 E_{t-1} + \varepsilon_f \]  

Then the Multivariate Vector Error Correction GARCH model is given by:

\[
\begin{bmatrix}
    h_{t,t}^{ss} \\
    h_{t,t}^{sf} \\
    h_{t,t}^{ff}
\end{bmatrix} =
\begin{bmatrix}
    c_{tt}^{ss} \\
    c_{tt}^{sf} \\
    c_{tt}^{ff}
\end{bmatrix} +
\begin{bmatrix}
    a_{11} & a_{12} & a_{13} \\
    a_{21} & a_{22} & a_{23} \\
    a_{31} & a_{32} & a_{33}
\end{bmatrix} 
\times
\begin{bmatrix}
    \varepsilon_{s,t-1}^2 \\
    \varepsilon_{s,t-1} \varepsilon_{f,t-1} \\
    \varepsilon_{f,t-1}^2
\end{bmatrix} +
\begin{bmatrix}
    b_{11} & b_{12} & b_{13} \\
    b_{21} & b_{22} & b_{23} \\
    b_{31} & b_{32} & b_{33}
\end{bmatrix} 
\times
\begin{bmatrix}
    h_{t,t}^{ss,t-1} \\
    h_{t,t}^{sf,t-1} \\
    h_{t,t}^{ff,t-1}
\end{bmatrix}
\]  

where \( h_{t,t}^{ss} \) and \( h_{t,t}^{ff} \) are the conditional variance of the errors \((\varepsilon_{s,t}, \varepsilon_{f,t})\) and \( h_{t,t}^{sf} \) is the conditional covariance series between spot and futures prices. This multivariate GARCH model takes into account a time-varying conditional correlation coefficient between the spot and futures prices. Hence it generates more accurate time varying hedge ratios.

### 3.3 Hedging effectiveness

Four different models have been used to estimate optimal hedge ratios for our data set. Then the hedging performances of the four different strategies are evaluated and compared both in-sample and out-of-sample.

According to Kroner and Sultan (1993), the variances of the return of the unhedged and hedged portfolio are calculated as:

\[ Var(U) = \sigma_s^2 \]

\[ Var(H) = \sigma_s^2 + h \sigma_f^2 - 2 h \sigma_{sf} \]

where \( Var(U) \) and \( Var(H) \) represent variance of unhedged and hedged portfolios, \( \sigma_s \) and \( \sigma_f \) are the standard deviation of the spot and futures price, respectively, and \( \sigma_{s,f} \)
represents the covariance of the spot and futures price series, and $h^*$ is the optimal hedge ratio calculated following our four models.

According to Ederington (1979), the effectiveness of hedging can be assessed as the percentage reduction in the variance of the hedged portfolio relative to the unhedged portfolio. The variance reduction can be calculated as:

$$\tau = \frac{Var(U) - Var(H)}{Var(U)}$$

Since Lien and Tse (1998) propose that the hedging performance of the models may vary over different hedge periods, in this project, we compare the hedging effectiveness of four types of hedge ratios over in-sample and out-of-sample hedge periods. The out-of-sample analysis is conducted for the period from January 19, 2006 to March 1, 2006. For the GARCH model which has time varying hedge ratios, in the out-of-sample test, we forecast the following day hedge ratio by calculating the ratio of the one period forecast of the variance to the one period forecast of the conditional variance. On the other hand, we use the estimated hedge ratios in the out-of-sample period for the other three models whose hedge ratios are constant.

In the next section we use Matlab to program our four models discussed previously to compute their hedge ratios and hedging performance.
4 EMPIRICAL RESULTS

4.1 Estimations from OLS model

In this section, we present results from the OLS model. We start with Table 4.1 which displays the descriptive statistics of spot and futures price of GBPUSD logarithmic series. Table 4.1 presents the descriptive statistics from the OLS method by running the regression equation: 

\[ \Delta S_t = \alpha + \beta \Delta F_t + \epsilon_t \]

As we know that Kurtosis of 3 represents the normal distribution. The high Kurtosis 4.3869 of the log Spot Price and 4.4583 of the log Futures Price which are greater than 3 adequately demonstrate that they do not follow a normal distribution.

Table 4.1 Descriptive Statistics of spot price and futures price of GBPUSD Logarithmic Series

<table>
<thead>
<tr>
<th></th>
<th>Spot Price ((\Delta S))</th>
<th>Futures Price ((\Delta F))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3.9154e-005</td>
<td>3.9315e-005</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0049</td>
<td>0.0051</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.0228</td>
<td>-0.0266</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0246</td>
<td>0.0267</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.0164</td>
<td>-0.0244</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.3869</td>
<td>4.4583</td>
</tr>
</tbody>
</table>

Table 4.2 shows the estimated coefficients of the regression. From Table 4.2 we can see that the optimal hedge ratio is: \(h^* = 0.7415\) which means that we should buy 0.7145 futures contracts to hedge the market risk of 1 underlying currency. Table 4.2, which also provides each coefficient’s t-ratios at the 5%-level, shows that the intercept is insignificant. This means there is no linear relationship in the regression.
Table 4.2 Estimates of the conventional regression model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>T-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.0129e-005</td>
<td>0.1716</td>
</tr>
<tr>
<td>ΔFt (hedge ratio)</td>
<td>0.7415</td>
<td>64.3260</td>
</tr>
</tbody>
</table>

Since we have discussed in the model section that the estimated hedge ratio may be inaccurate if there is some serial correlation, a Durbin-Watson test is conducted in order to assess the importance of serial correlation. The Durbin-Watson test included in Table 4.3 shows that there is serial correlation. This means that the coefficient estimates are inaccurate. Furthermore we can also interpret the presence of serial residuals as a sign that the OLS model does not model the dependent variable accurately. Next, the high Bera-Jarque statistic we obtained shows that the residuals do not follow a normal distribution. This result also implies that the coefficient estimates may be not reliable.

Table 4.3 Results of the diagnostic tests conducted on model 1

<table>
<thead>
<tr>
<th>Test</th>
<th>Test Statistic</th>
<th>P-Value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normality: Jarque-Bera</td>
<td>258.85</td>
<td>0.01225</td>
<td>Not normal</td>
</tr>
<tr>
<td>Serial Correlation: Durbin-Watson</td>
<td>2.7964</td>
<td>0.00000</td>
<td>Correlated</td>
</tr>
</tbody>
</table>

In conclusion, the results obtained from the OLS model imply that the regression models could be misspecified and that the coefficient estimates (optimal hedge ratios) may be wrong.

4.2 Estimations from VAR model

The previous sub-section shows results from OLS model. In this sub-section we present the results from a different model-Vector Autoregressive (VAR) model. As we discussed previously, the OLS model does not take into account serial correlation. This is a problem because if serial correlation is present in our data, our least squares estimator will still be
longer B.L.U.E. (Best Linear Unbiased Estimation). In other words, serial correlation does affect efficiency. Moreover, in the case of positive serial correlation, this loss of efficiency will be masked by the fact that the estimates of the standard errors obtained from the least-squares regression will be smaller than the true standard errors (i.e. they will be biased downward). Yang (2001) solves this problem by introducing the Vector Autoregressive (VAR) model shown in equation (3) and equation (4).

Because the variance of estimators may be inversely proportional to the number of degrees of freedom, we use the information criteria to solve this problem. Here we use the multivariate version of Akaike’s information criterion (AIC) and Schwarz Bayesian information criterion (BIC) to decide on the optimal number of lags. Information criteria have two factors: a term which is a function of the residual sum of squares (RSS), and a penalty term for the loss of degrees of freedom from adding extra parameters. So, adding a new variable or an additional lag to a model will have two competing effects on the information criteria: the residual sum of squares will fall but the value of the penalty term will increase\(^5\). Therefore, the object is to choose the number of parameters which minimizes the value of the information criteria.

Table 4.4 shows the values of Akaike’s and Schwarz’s information criteria from 1 lag to 7 lags. It is clear that both AIC and BIC are minimized at 6 lags of each variable. Hence, we conduct the subsequent analysis using a VAR (6) model. Table 4.5 displays the estimated coefficients of the regression.

Table 4.4 Values of the multivariate version of the Akaike’s (AIC) and Schwartz’s Bayesian (BIC) information criteria for different number of lags in VAR model

<table>
<thead>
<tr>
<th>Lags</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.014676</td>
<td>-0.012603</td>
</tr>
<tr>
<td>2</td>
<td>-0.001416</td>
<td>0.002731</td>
</tr>
<tr>
<td>3</td>
<td>0.018819</td>
<td>0.025038</td>
</tr>
<tr>
<td>4</td>
<td>-0.000364</td>
<td>0.007929</td>
</tr>
<tr>
<td>5</td>
<td>0.054412</td>
<td>0.064778</td>
</tr>
<tr>
<td>6</td>
<td>-0.016006*</td>
<td>-0.003567*</td>
</tr>
<tr>
<td>7</td>
<td>-0.009753</td>
<td>0.004760</td>
</tr>
</tbody>
</table>

Note: "*" indicates the minimum for each information criterion.

Table 4.5 Estimated Parameters from VAR (6) Model

<table>
<thead>
<tr>
<th></th>
<th>1 lag</th>
<th>2 lags</th>
<th>3 lags</th>
<th>4 lags</th>
<th>5 lags</th>
<th>6 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s$</td>
<td></td>
<td>0.0374</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta s$</td>
<td>1.9114</td>
<td>0.9800</td>
<td>3.1169</td>
<td>1.0621</td>
<td>2.7092</td>
<td>0.9634</td>
</tr>
<tr>
<td>$\gamma s$</td>
<td>-1.0083</td>
<td>1.0736</td>
<td>-1.3284</td>
<td>0.4148</td>
<td>1.4590</td>
<td>-0.6082</td>
</tr>
<tr>
<td>$\sigma f$</td>
<td>0.1080</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta f$</td>
<td>0.6920</td>
<td>-0.7201</td>
<td>7.9819</td>
<td>4.9511</td>
<td>1.3297</td>
<td>0.3569</td>
</tr>
<tr>
<td>$\gamma f$</td>
<td>-2.5459</td>
<td>-0.1937</td>
<td>-0.8139</td>
<td>-0.6631</td>
<td>1.5737</td>
<td>2.6448</td>
</tr>
<tr>
<td>$\sigma sf$</td>
<td></td>
<td></td>
<td>1.0e-004 * 0.1944</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma ff$</td>
<td></td>
<td></td>
<td>1.0e-004 * 0.2618</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma sf/\sigma ff$</td>
<td></td>
<td></td>
<td>0.74259</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The tests for autocorrelation are now conducted to verify the persistence of this problem. The Durbin-Watson test is displayed in Table 4.6. Since the DW value 1.9977 is so close to 2, we can accept the null hypothesis that there is no serial correlation. In other words the VAR (6) model has adequately taken into account the serial correlation previously detected.

The VAR model also does not test the cointegration relationship between the variables. Table 4.6 displays the results for the Durbin-Watson test. Since the DW value of 1.9977 is greater
than the critical value of 0.511, we can reject the hypothesis of no co-integration at the 1-percent level. In other words the spot and futures currency prices are cointegrated.

Table 4.6 Co-integration Test for the Spot Price and Futures Price

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Critical Value (1%)</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>DURBIN-WATSON</td>
<td>1.9977</td>
<td>0.511</td>
<td>Co-integrated</td>
</tr>
</tbody>
</table>

Note: Durbin-Watson test both serial correlation and cointegration.

4.3 Estimations from VECM model

From Section 4.2 we know that the spot and futures currency prices are cointegrated at 1-percent level. Hence the optimal hedge ratio estimated from VAR model from last section may be wrong. In order to overcome this problem, in this section we incorporate the cointegrating vector in the VAR to obtain a Vector Error Correction Model. The results from VECM are presented in Table 4.7.

From Table 4.7 we can see that the t statistics of -3.0241 and -3.8413 of the coefficients $\alpha_s$ and $\alpha_f$ of the error correction term are significant at 5% level, we can draw the conclusion that the error correction term is correctly added in both equations (8) and equation (9).

Since $\alpha_s$ and $\alpha_f$ are the coefficients of the error correction term from equation (8) and equation (9), their absolute value represents the speed of the spot and futures market responds to the deviation from the long term stability relationship. Because the absolute value of $\alpha_s$ of -0.0164 is greater than the absolute value of $\alpha_f$ of -0.0134, the spot prices have a little faster speed of adjustment than the futures prices. Hence this shows that there may be a small bi-direction existing between the spot and futures prices markets.
Table 4.7 Estimated Parameters from VECM Model

<table>
<thead>
<tr>
<th></th>
<th>1 lag</th>
<th>2 lags</th>
<th>3 lags</th>
<th>4 lags</th>
<th>5 lags</th>
<th>6 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>cs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1010</td>
</tr>
<tr>
<td>βs</td>
<td>1.9098</td>
<td>5.0721</td>
<td>4.3943</td>
<td>2.1911</td>
<td>-2.1085</td>
<td>2.6167</td>
</tr>
<tr>
<td>ρs</td>
<td>1.4182</td>
<td>0.5878</td>
<td>3.1939</td>
<td>0.0020</td>
<td>-1.0911</td>
<td>-4.1145</td>
</tr>
<tr>
<td>αs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0164 (t-ratio -3.0241)*</td>
<td></td>
</tr>
<tr>
<td>cr</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0190</td>
<td></td>
</tr>
<tr>
<td>βf</td>
<td>0.1581</td>
<td>1.3325</td>
<td>-0.3869</td>
<td>2.1890</td>
<td>7.9379</td>
<td>0.5638</td>
</tr>
<tr>
<td>γf</td>
<td>1.1156</td>
<td>1.7575</td>
<td>-0.3223</td>
<td>-0.0240</td>
<td>-1.0678</td>
<td>-1.4574</td>
</tr>
<tr>
<td>αf</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0134 (t-ratio -3.8413)*</td>
<td></td>
</tr>
<tr>
<td>σsf</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.9437e-005</td>
<td></td>
</tr>
<tr>
<td>σff</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.6174e-005</td>
<td></td>
</tr>
<tr>
<td>σsf/σff</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.74263</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (a) The results are the estimates of equations (8) and equation (9) from lag 1 to lag 6. (b)*indicates the statistically significant coefficients at 5% level.

4.4 Estimations from multivariate GARCH with the error correction model

We have already seen that the VAR model has successfully considered the serial correlation in the residuals. However, Figure 1 of the residuals shows that even if the mean seems constant, the variance is still changing through time and the autoregressive conditional heteroskedasticity (ARCH) exists. Because of the heteroscedasticity, the assumption of a constant variance over time is untrue in practice and the estimation of constant hedge ratios could be wrong. Therefore we employ time-varying variances and covariances in the GARCH model in order to get time-varying hedge ratios. These are expected to give better hedging effectiveness.

The multivariate GARCH model is given by equations (10), (11) and (12). The estimation results from Model 4, the Multivariate GARCH with error correction model that focuses on modelling the conditional variances and covariances of residuals from the VECM, are presented in Table 4.8. The results in Table 4.8 show that all coefficients are statistically
significant. This implies that current information is important for forecasting conditional variances at all horizons. From the significant estimated parameters we can draw the conclusion that the GARCH error is able to capture the dynamics in the variances of the joint distribution of returns.

Table 4.8 Estimated Parameters from multivariate GARCH with error correction model

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>css</th>
<th>csf</th>
<th>cff</th>
<th>βss</th>
<th>βsf</th>
<th>βff</th>
<th>ass</th>
<th>asf</th>
<th>aff</th>
</tr>
</thead>
<tbody>
<tr>
<td>z-statistics</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1798</td>
<td>-0.0238</td>
<td>0.1798</td>
<td>1.5020</td>
<td>1.3934</td>
<td>1.5020</td>
</tr>
</tbody>
</table>

Notes: (a) css, csf and cff are constants. βss, βsf and βff are coefficients of the conditional variances and covariances, respectively. ass, asf and aff are coefficients of the squared error terms, respectively. (b) The results are estimated from equation (10), equation (11) and equation (12).

Table 4.9 shows the description of the distribution of dynamic hedge ratios obtained from the time-varying conditional variance and covariance between spot and futures price changes and Figure 2 and Figure 3 plot this distribution. The hedge ratio ranges from a minimum of 0.0019 to a maximum of 1.9945. The dynamic hedge ratio series has a sample mean of 0.8485, which is smaller than 1, but greater than the constant hedge ratio estimates obtained from the other three models of 0.74. These estimates suggest that the naïve hedging strategy is inappropriate. With a standard deviation of 0.4004, skewness of 0.5945 and kurtosis of 3.3515, this hedge ratio series does not follow a normal distribution, as suggested by the Jarque-Bera test statistic of 183.8915. However, it is stationary over the sample period with a Dicky-Fuller test statistic of -13.689.
Table 4.9 Distribution of Hedge Ratio from multivariate GARCH with error correction model

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.8485</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.4004</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.0019</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.9945</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.5945</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.3515</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>183.8915</td>
</tr>
<tr>
<td>Dicky-Fuller</td>
<td>-13.689</td>
</tr>
</tbody>
</table>
5 HEDGING EFFECTIVENESS

In this section, we evaluate and compare the hedging effectiveness of four hedging models discussed previously and the naïve hedge which assumes a unitary hedge ratio.

The hedge ratio for the OLS model is calculated as the estimated coefficient of the futures price in the regression of spot on the futures price. In the VAR and VECM models, we use the ratio of the variance to the covariance of the residuals to obtain the optimal hedge ratios. The optimal hedge ratios for these three models are presented in Table 5.1. From this table it can be seen that the hedge ratio of 0.74263 obtained from the VEC model is slightly higher than the hedge ratio of 0.7415 of OLS and 0.74259 of VAR models.

Figure 2 plots the dynamic hedge ratio of the conditional variance to covariance between spot and futures price from the multivariate GARCH with error correction model. From this figure we can see signs of extreme volatility during the sample period. The mean of the hedge ratio is 0.8485 while the range varies from a minimum of 0.0019 to a maximum of 1.9945.

Table 5.1 Optimal hedge ratio for the OLS, VAR, VECM and multivariate GARCH with error correlation model

<table>
<thead>
<tr>
<th>Model</th>
<th>OLS</th>
<th>VAR</th>
<th>VECM</th>
<th>GARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal hedge ratio</td>
<td>0.74150</td>
<td>0.74259</td>
<td>0.74263</td>
<td>0.84850</td>
</tr>
</tbody>
</table>

Table 5.2 displays the in-sample hedging performance of the 5 models. The naïve method is added for comparison. Because the variances of all 5 models are higher than the unhedged
position, we can draw the conclusion that all 5 hedging strategies have risk reductions compared to the unhedged position.

In detail, the unhedged portfolio suffers from the highest variance in the return. The naïve hedge whose hedge ratio is 1 follows the smallest variance reduction relative to the unhedged position equal to 92.66%. The variance reduction percentages for the remaining models do not differ very much. The multivariate GARCH with error correction model offers a slightly higher variance reduction percentage than those of the OLS, the VAR and the VECM models. Indeed the variance reduction provided by the GARCH model is 93.34% compared to the 93.28% of the OLS model, the 93.33% of the VAR model and the 93.33% of the VECM model. In conclusion, in this project, the hedging performances of all four strategies do not differ very much.

Table 5.2 In-sample hedging performance

<table>
<thead>
<tr>
<th>Model</th>
<th>Variance</th>
<th>% Variance Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unheded</td>
<td>0.01490000</td>
<td></td>
</tr>
<tr>
<td>OLS</td>
<td>0.00100150</td>
<td>0.93279</td>
</tr>
<tr>
<td>VAR</td>
<td>0.00099319</td>
<td>0.93334</td>
</tr>
<tr>
<td>VECM</td>
<td>0.00099317</td>
<td>0.93334</td>
</tr>
<tr>
<td>GARCH</td>
<td>0.00099206</td>
<td>0.93342</td>
</tr>
<tr>
<td>NAIVE</td>
<td>0.00109333</td>
<td>0.92662</td>
</tr>
</tbody>
</table>

Table 5.3 displays the out-of-sample comparison conducted for the last thirty observations. Although all the models provide lower variance reduction terms than those of in-sample portfolios, the results are consistent which means that the hedging performances of all four strategies do not differ very much.
Table 5.3  Out of sample hedging performance

<table>
<thead>
<tr>
<th>Model</th>
<th>Variance</th>
<th>% Variance</th>
<th>Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unhedged</td>
<td>3.1064e-004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLS</td>
<td>3.5786e-005</td>
<td>0.88480</td>
<td></td>
</tr>
<tr>
<td>VAR</td>
<td>3.5609e-005</td>
<td>0.88537</td>
<td></td>
</tr>
<tr>
<td>VECM</td>
<td>3.5608e-005</td>
<td>0.88537</td>
<td></td>
</tr>
<tr>
<td>GARCH</td>
<td>3.5013e-005</td>
<td>0.88729</td>
<td></td>
</tr>
<tr>
<td>NAÏVE</td>
<td>3.9673 e-005</td>
<td>0.87229</td>
<td></td>
</tr>
</tbody>
</table>
6 CONCLUSIONS

This study has empirically measured the appropriateness of four hedging models with spot and futures exchange rates of the British Pound. We use the first 2,878 observations in the test and leave the last 30 observations for out-of-sample hedge ratio performance comparison.

The hedging performances obtained from the conventional OLS model, the VAR model, the VECM model, and the multivariate GARCH with error correction model are compared in terms of variance minimization.

The hedging performances of the hedge ratios of in-sample and out-of-sample portfolios offer a similar result. All four models and the naïve model give a significant variance reduction compared to the unhedged position. The VAR model and the VECM offer the same performance, which is a little higher than that of the OLS model. This is reasonable because considering the presence of heteroscedasticity and the existence of a cointegrating relationship between spot and futures markets, the inclusion of an error correction term in the model should give better results. Although the multivariate GARCH with error correction model is the only one being able to capture the time varying nature of the hedge ratio, the hedging performances of all four strategies do not differ very much, either in-sample or out-of-sample. This result is consistent with Myers (1991) and Miffre (2001).

Thus, at first glance, applying a dynamic GARCH framework could seem reasonable because of the presence of heteroscedasticity and cointegration between spot and futures markets. However, since the hedging performances of all four strategies do not differ very much, the consideration of the extra computation with a GARCH model could be meaningless.
Since this is only a result based on a single exchange rate, the GARCH model may provide significantly better performance with other types of futures. However, we should not underestimate this consideration, because previous studies (Myers, 1991; Miffre, 2001) draw the same result. For example Myers (1991, p.40) writes that “the extra expense and complexity of the GARCH model do not appear to be warranted”.

In conclusion, in this project, the hedging performances of all four strategies do not differ very much. Whether similar conclusion will be drawn from other types of futures remains an empirical question. At the same time, the transaction costs in adjusting the hedged portfolio also need to be considered. These two questions are left to future research.
APPENDICES

Appendix A

Figure 1  The plot of the residuals from the VAR Error Correction Model

Figure 2  Distribution of Hedge Ratio from GARCH Model
Figure 3  Distribution of Hedge Ratio from GARCH Model

Figure 4  Distribution of Hedge Effectiveness from GARCH Model
REFERENCE LIST


