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Futures Hedging Effectiveness with the Information of Implied Volatility Index

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Abstract. This study outlines and compares approaches for estimating time-varying optimal hedge ratios with or without implied volatility on futures markets. These time-varying methods are applied to compare the outcomes using out-of-sample performance evaluations. The hedging performance for the models with IV outperfom the traditional models without IV under out-of-sample analysis. This finding is valuable in the sense that it suggests that the investors may need to adjust their hedging strategies using different hedging models and taking IV into account according to the trend or patterns of price movements.

Keywords: Hedging Effectiveness, Implied Volatility, Multivariate GARCH

1 Introduction

The price movements in spot markets are highly volatile all over the world and may go down at any time. To reduce the price uncertainty of the underlying assets, futures contracts can be a very effective risk management instrument for investors due to its high liquidity and low transaction cost. Many theoretical methods have been used in previous studies to determine the optimal futures position by minimizing the variance of the spot- futures portfolio and estimate the optimal hedge ratios (Johnson, 1960; Ederington, 1979).

However, among the literature, the most effective hedging ratios were only obtained through various econometric models without considering the influence of investors' sentiment and market volatility. In this study, we attempt to improve the effectiveness of hedging by taking implied volatility into account.

Implied volatility indices (IV) have been considered by market participants as important tools for measuring investors' sentiment and market volatility. The computation of IV takes into account the latest advances in financial theory, eliminating measurement errors that had characterized implied volatility measures. IV may be a priced risk factor for security returns and it may be necessary to consider broader measures of IV than those that have traditionally been studied. Therefore, the implied volatility measures are regarded as informative variables for forecasting the next day's volatility (Becker et al., 2007).

2 Methodology

The optimal hedge ratio is measured as the slope coefficient in a regression of the rate of return the unhedged spot position on the rate of return on the hedging instrument. The minimum-variance (MV) hedge ratio is one of the most commonly adopted hedging strategies. The MV hedge ratio introduced by Johnson (1960) is based on minimizing the variance of the hedged portfolio. The MV hedge ratio

is simple to understand and estimate. Defining that $R_{S,t}$ and $R_{F,t}$ are the spot and futures returns at a given time t, respectively, the optimal hedge ratio of h is as follows:

$$h = \frac{\sigma_{sf}}{\sigma_f^2} = \rho_{sf} \times \frac{\sigma_s}{\sigma_f} \tag{1}$$

where σ_{sf} denotes the covariance of $R_{S,t}$ and $R_{F,t}$, and σ_f^2 denotes the variance of $R_{F,t}$; ρ_{sf} represents the correlation coefficient of $R_{S,t}$ and $R_{F,t}$; σ_s, and σ_f are the standard deviations of $R_{S,t}$ and $R_{F,t}$, respectively.

2.1 OLS Model

The assumption that the variance-covariance matrix is time-invariant implies a constant hedge ratio over time, which leads to the conventional method of the least squares regression, specified as:

$$R_{S,t} = \alpha + hR_{F,t} + \varepsilon_t \tag{2}$$

where h is the optimal hedge ratio.

2.2 Multivariate GARCH (MGARCH) Models

In the application of computing the hedge ratio, a general form of the multivariate GARCH model is set as:

$$R_{S,t} = \alpha_s + \beta_s R_{F,t} + \theta_s \varepsilon_{s.t-1} + \varepsilon_{s,t} \tag{3.1}$$

$$R_{F,t} = \alpha_f + \beta_f R_{S,t} + \theta_f \varepsilon_{f.t-1} + \varepsilon_{f,t} \tag{3.2}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{bmatrix} \Bigg| \Omega_{t-1} \sim N\left(0, H_t\right) \tag{3.3}$$

$$H_t = \begin{bmatrix} \sigma_{s,t}^2 & \sigma_{sf,t} \\ \sigma_{sf,t} & \sigma_{f,t}^2 \end{bmatrix} \tag{3.4}$$

where H_t is a conditional variance-covariance matrix; Ω_{t-1} is the information set at

$t-1$. The moving average of degree one, MA(1) term, in the mean equation, is used to capture the bid–ask bounce effect. ε_t is assumed to follow student's t distribution with a degree of freedom υ. It appears that the MGARCH model allows the second moments of the joint distribution of the variables to change over time, which responds to the criticism of heteroscedasticity in the error terms of the OLS model. Accord to this formula, the time-varying hedge ratio can easily be obtained from the elements in H_t.

2.2.1 MD Model

A general form of two-variable multivariate GARCH (1,1) model is written as:

$$\text{vech}(H_t) = K + A\,\text{vech}(\varepsilon_{t-1}\varepsilon_{t-1}^{\mathrm{T}}) + B\,\text{vech}(H_{t-1}) \tag{4}$$

where K is a (3×1) parameter vector; both parameter matrix A and B are a (3×3) matrix. The vech(.) is the column stacking operator that stacks the lower triangular portion of a matrix. For a two-variable system, 21 parameters are in need of being estimated. By imposing the A and B as diagonal matrices, we obtain the simple diagonal vech GARCH model developed by Bollerslev et al. (1988). To guarantee a positive semi-definite (PSD) time-varying covariance matrices, Ding and Granger (1996) suggest to estimate H_t through a Cholesky decomposition:

$$H_t = KK^{\mathrm{T}} + AA^{\mathrm{T}} \otimes \varepsilon_{t-1}\varepsilon_{t-1}^{\mathrm{T}} + BB^{\mathrm{T}} \otimes H_{t-1} \tag{5}$$

where $\otimes$ denotes the Hadamard product, i.e., element-by-element multiplication; and where K, A, and B are all lower triangular matrices which guarantees that H_t positive is definite.

2.2.2 CCC Model

For parameter parsimony, Bollerslev (1990) suggested H_t be decomposed into a conditional constant correlation matrix and diagonal matrices of standard deviations, given by:

$$H_t = \begin{bmatrix} \sigma_{s,t}^2 & \sigma_{sf,t} \\ \sigma_{sf,t} & \sigma_{f,t}^2 \end{bmatrix} = \begin{bmatrix} \sigma_{s,t} & 0 \\ 0 & \sigma_{f,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sigma_{s,t} & 0 \\ 0 & \sigma_{f,t} \end{bmatrix} \tag{6}$$

where ρ denotes the correlation coefficient between $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$. This approach effectively transforms the multivariate time series into a univariate time series and then applies the univariate GARCH to each of the univariate series. The constant correlation matrix not only increases computational efficiency but also facilitates identification of the PSD covariance matrix.

2.2.3 BEKK Model

The BEKK model (following Bollerslev, Engle, Kroner, and Kraft) model developed by Engle and Kroner (1995), is specified in the more general form:

$$H_t = KK^{\mathrm{T}} + A\varepsilon_{t-1}\varepsilon_{t-1}^{\mathrm{T}}A^{\mathrm{T}} + BH_{t-1}B^{\mathrm{T}} \tag{7}$$

where K is a lower triangular matrix; A and B are unrestricted squared matrices. It can be shown that the above quadratic form guarantees a symmetry and a PSD variance-covariance matrix.

2.3 IV with MGARCH Models

This study examines the benefits of combining IV with MGARCH models. This is done by including IV as an exogenous variable in the variance equation. Since IV has been considered by many to be the world's premier barometer of investor sentiment and market volatility, which may be able to provide more information while calculate the optimal hedge ratio.

2.4 Hedging Performance Measure

The purpose of futures hedging is to reduce the variance of the returns of the hedged portfolio. A conventional measure of hedging effectiveness is computed by the percentage of risk reduction as follows:

$$HE = \frac{\sigma_{R_u} - \sigma_{R_h}}{\sigma_{R_u}} = 1 - \frac{\sigma_{R_h}}{\sigma_{R_u}} \tag{8}$$

where R_h is the return of the hedged portfolio defined by $R_h = R_s - h \times R_f$, and where R_u is the return of the unhedged spot position. The closer the HE is to 1, the higher the degree of hedging effectiveness.

3 Data and Empirical Results

Daily spot prices, futures prices and implied volatility indices ranging from August 24, 2005 to December 31, 201s. The data set consists of the spot price indices of Germany (DAX Index), the UK (FTSE 100 Index), and the US (S&P 500 Composite Index). All the national stock-price indices are in local currency, dividend-unadjusted, and based on daily closing prices in each national market. Futures contracts with the rolling period of a week prior to expiration of the current contracts to the next contract are used to circumvent the effects of thin markets and expiration.

The out-of-sample hedging strategies are derived dynamically from each econometric model using a rolling window of 250 business days (approximately one year). The rationale behind the out-of-sample analysis is that the parameters in each model are re-estimated for each decision node once new information is arrived, which helps to better trace the price pattern. This method is also based on the concept that the hedgers are able to use only historical data to precede the hedge ratio while updating their strategies as soon as new information is observed. In general, the hedging effectiveness measured by a standard deviation reduction makes a difference for those given by the in-sample analysis. Therefore, the hedging effectiveness for the out-of-sample is more reliable and better applicable in practice. The empirical results of the out-of-sample analysis are presented in Table 1.

The hedging performance for most of the models with IV outperfom the traditional models without IV under out-of-sample analysis. This finding is valuable in the sense that it suggests that the investors may need to adjust their hedging strategies with the consideration the effect of implied volatility. The investors shall also consider using different hedging models according to the trend or patterns of price movements in different markets. BEKK model with IV is the optimal hedging model.

Table 1 Comparison of out-of-sample hedging effectiveness

	OLS	MD	CCC	BEKK
DAX				
Traditional	0.819	0.811	0.813	0.810
with IV		0.819	0.813	**0.820**
FTSE				
Traditional	0.781	0.783	0.779	0.780
with IV		0.783	0.779	**0.783**
S&P500				
Traditional	0.809	0.813	0.811	0.811
with IV	-	0.816	0.810	**0.816**

4 Conclusions

This study outlines and compares approaches for estimating time-varying optimal hedge ratios with or without implied volatility on futures markets. These time-varying methods are applied to compare the outcomes using out-of-sample performance evaluations. The hedging performance for most of the models with IV outperfom the traditional models without IV under out-of-sample analysi. This finding is valuable in the sense that it suggests that the investors may need to adjust their hedging strategies using different hedging models according to the trend or patterns of price movements. The factor causing the differences, however, is beyond the discussion of our study, which nevertheless provides a start for further research.

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