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Returns and Volatility Spillover Between the Kuala Lumpur Stock Index and Kuala Lumpur Futures Index: Bivariate GARCH Model

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***Abstract*:** This article investigates the effectiveness of hedging the cash markets index on the KLSE using the futures index on the MDEX. By the application of the bivariate GARCH(1, 1) model, the time varying hedge ratio is able to capture the volatility spillover between the two markets. The results show that the two models show an obvious disparity in the variance of the hedged portfolio when the economy is in the 1997 financial crisis. The implication to investors is that it is still too risky to enter the market even with a hedged portfolio during a financial crises. Thus, hedging the cash market using futures to reduce investment risk fails when it is most needed. The implications of these results are very important to hedgers. These include the optimal hedge ratio and the risk involved in hedging itself especially during a period of financial crisis.

Keywords: Bi-GARCH, hedging, optimal hedge ratio

1. Introduction

The relationship between stock and futures market returns have been intensively investigated in empirical research. These include topics in areas of pricing the futures, the lead-lag effect of cash and futures prices and the effectiveness of hedging using the futures. However, there is no conclusive evidence on the behaviour of the relationship. Harris (1989) even found that the cash and the futures markets are not cointegrated for the S&P500 index. This result is further supported by findings reported by Fortenbery and Zappa (1997), and Antoniou and Garret (1993) for the British stock market. For the Malaysian market in particular, Ibrahim *et al.* (1999) found "...no evidence of any increase in the volatility of the underlying stock market index as a result of futures introduction."

In the lead-lag effect of futures and cash markets, studies by Kawaller *et al.* (1987), Stoll and Whaley (1990) and Chan (1992) found that the futures market leads the cash market. Kawaller *et al.* (1987) conclude that the S&P 500 futures leads the Index by 20 to 45 minutes and the reverse is a weak one.

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Some studies have shown that the leading role of the futures market is only half of the story. Fung and Leung (1993) found that there exists a two-way causality in the cash and futures for the Eurodollar deposits. This two-way causality also exists for Municipal Bond Index (Hung and Zhang 1995), with the futures market showing a stronger leading role. Contradicting this finding, a stronger feedback from spot-to-futures was found by Wahab and Lashgari (1993) in their study on the S&P500 and the FT-SE100 indexes. Shyy *et al.* (1996) on the other hand found that for the Paris Bourse, the cash index leads the stock index futures traded on the Matif and the relationship is unidirectional.

Ross (1989) concludes that the variance of the price change can be interpreted as the rate of arrival of information. The variance or the volatility of the price change in one market may have a spillover effect on other markets due to the realisation that speculative price changes are interwoven with higher moment dependencies (Bollerslev *et al.* 1992). Chan *et al.* (1991) further cautions researchers in ignoring the spillover effect of volatility in studying the relationship between the cash and the futures markets. They show that ignoring the volatility effect can lead to specification error and incorrect inference of the relationships. Thus ignoring the volatility spillover ignores the effect of information transmission between the two markets.

This paper provides an empirical investigation of the dynamic interdependence of the cash and the futures markets and an analysis on the effect of using the futures market in hedging the cash market. This is done by considering the variance of portfolio consisting of the cash and the futures markets. The spillover effects of the two markets are captured by using bivariate generalised autoregressive conditional heteroskedasticity model (bivariate GARCH) proposed by Bollerslev (1986). The use of this model enables us to capture some characteristics of returns that are often ignored in empirical studies. These include leptokurtosis, skewness and volatility clustering. The bivariate GARCH model also enables us to capture the spillover of volatility and the dynamics of the conditional variance by estimating the parameters for the two markets simultaneously. This helps us avoid model misspecification as discussed by Chan *et al.* (1991). We then show how these results can be used for hedging purposes in the cash market. Comparison will be made to the conventional way of calculating the hedging of the cash market using the GARCH model instead of the bivariate GARCH model.

2. Data Description and Preliminary Analysis

In this paper we used the data from the Kuala Lumpur Stock Exchange (KLSE) and the Malaysian Derivatives Exchange (MDEX). Daily data spanning from October 1996 to June 2000 and January 2004 to March 2008 for the Kuala Lumpur Composite Index (KLCI) and the Index Futures (KLFI) closing data were used. We used the daily data mainly due to the availability and following Hatemi and Roca (2006) in their study for the Australian market.

The descriptive statistics in Table 1 show the long right tail and the leptokurtic characteristics of the returns. The Jarque-Bera normality test rejects the null hypothesis of normally. Thus the results from this preliminary tests accord well with the concerns regarding returns as indicated by Ross (1989), Bollerslev *et al.* (1992) and Chan *et al.* (1991). We next proceed to the bivariate GARCH model.

Table 1. Descriptive statistics of index and futures returns

Statistic	October 1996 to June 2000		January 2004 to March 2008	
	Index	Futures	Index	Futures
Mean	0.0002	0.0003	0.0005	0.0005
Median	-0.0006	-0.0007	0.0007	0.0006
Maximum	0.2314	0.3335	0.0435	0.0495
Minimum	-0.2146	-0.3219	-0.0950	-0.0729
Std. Dev.	0.0240	0.0298	0.0084	0.0110
Skewness	1.4485	0.8656	-1.8240	-0.7584
Kurtosis	28.2265	34.5947	22.0147	8.4209
Jarque-Bera	29363	45597	16400	1386
Probability	0.0000	0.0000	0.0000	0.0000

3. Methodology

In this section, we explain the bivariate GARCH methodology. This paper also uses the conventional method of analysis for portfolio hedging. The standard non-linear GARCH(p,q) model is given by a single mean equation and a single variance equation. It is normally used in papers that study the volatility of variables that are conditionally affected by previous volatility and previous forecast errors. The cash and the futures markets seem to move together and are found to be cointegrated. For effective hedging using the futures market, we need to calculate the hedging ratio and check the volatility of our portfolio that comprises assets in the cash and the futures markets. The conventional (univariate) GARCH(1,1) has been used extensively in finance papers to study volatility. The model is represented as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i x_i + \varepsilon_t \quad \text{...... the mean equation}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \mu \quad \text{...... the variance equation}$$

Thus, in the conventional (univariate) method we use:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \mu \tag{1}$$

The above nonlinear GARCH(1,1) model will be run for KLCI and KLFI separately (hereafter will be referred to as S and F respectively). For hedging purposes, we need to know the hedging ratio b, which is calculated by the following regression:

$$S_t = \alpha_0 + \beta F_t + \varepsilon_t \tag{2}$$

The performance of the hedge can be constructed by considering the implied portfolio using the optimal beta calculated above and calculating the variance of the portfolio. The portfolio used is the standard 'textbook' portfolio:

$$(S_t - \beta_t F_t). \tag{3a}$$

Thus the variance of the portfolio is:

$$\text{Var}\,(S_t - \beta_t F_t). \tag{3b}$$

where the variances of S_t and F_t are obtained from the conditional variances in the variance equations above.

The bivariate GARCH(p,q) model is also a non linear estimation where the variances of the errors are assumed to be influenced conditionally by the previous forecast errors and previous volatility. However, the bivariate GARCH model extends the standard GARCH(p,q) model by considering multiple equations in both the mean and the variance equations. The system of equations also includes a covariance equation which captures the volatility spillover of the two markets. Thus we can look at the bivariate GARCH as a multiple equation version of the standard GARCH model.

We can use the bivariate GARCH model to specify the relationship between the cash and the futures markets. The theory underlying the bivariate GARCH model is similar to the standard GARCH, except for the multiple equations and the computation of parameters involved which can be a bit more complicated. The complication arises in the spillover effect that exists in all equations. We present the model for the bivariate GARCH(1,1) that is used in this paper.

$$S_t = \alpha_{11} + \alpha_{12} S_{t-1} + \alpha_{13} F_{t-1} + \varepsilon_{s,t} \quad \text{... spot mean equation}$$

$$F_t = \alpha_{21} + \alpha_{22} S_{t-1} + \alpha_{23} F_{t-1} + \varepsilon_{f,t} \quad \text{... futures mean equation}$$

$$h_{s,t} = \beta_{11} + \beta_{12} h_{s,t-1} + \beta_{13} \varepsilon^2_{s,t-1} + \mu_{s,t} \quad \text{... spot variance equation}$$

$$h_{f,t} = \beta_{21} + \beta_{22} h_{f,t-1} + \beta_{23} \varepsilon^2_{f,t-1} + \mu_{f,t} \quad \text{... futures variance equation}$$

$$h_{sf,t} = \beta_{31} + \beta_{32} h_{sf,t-1} + \beta_{33} \varepsilon_{s,t-1} \varepsilon_{f,t-1} + \mu_{sf,t} \quad \text{... covariance equation} \tag{4}$$

$$\varepsilon | I_{t-1} = \begin{bmatrix} \varepsilon_{s,t} | I_{t-1} \\ \varepsilon_{f,t} | I_{t-1} \end{bmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, H_t \right)$$

$$H_t = \begin{bmatrix} Var(\varepsilon_{s,t} | I_{t-1}) & Cov(\varepsilon_{s,t} \varepsilon_{f,t} | I_{t-1}) \\ Cov(\varepsilon_{s,t} \varepsilon_{f,t} | I_{t-1}) & Var(\varepsilon_{f,t} | I_{t-1}) \end{bmatrix}$$

The bivariate GARCH(1,1) model is estimated by maximising the following log-likelihood equation:

$$L(\theta) = -T \ln(2\pi) - (1/2) \sum_{t=1}^{T} (\ln |H_t(\theta)| + \varepsilon_t(\theta) H_t^{-1}(\theta) \varepsilon_t'(\theta)) \tag{5}$$

The results from the bivariate GARCH model can then be used to find the beta or the dynamic hedge ratio at time t which is calculated as the ratio of the conditional covariance between the cash and the futures market return to the conditional variance of the futures market return:

$$\beta_t^* = \frac{h_{sf,t}}{h_{f,t}}. \quad (6)$$

Similarly, the variance of the portfolio is Var $(S_t - \beta_t^* F_t)$.

4. Results

In the analysis of the conventional GARCH(1,1) and bivariate GARCH(1,1) model, we analysed the data assuming they are continuous in time series data (undated) since the GARCH model cannot handle missing dates. Thus the dates were converted to observations assuming there were no missing data. We used the return data and they are all free from non stationarity. However, the error term in the mean equations was found to be autocorrelated and to correct this, autoregressive term [ar(1)] is added to all the mean equations. The results of the conventional GARCH(1,1) model is reported in Table 2.

From Table 2, the value of the hedge ratio b is 0.730192. To calculate the variance of the portfolio in (3a), we used the conditional variances from Tables 3 and 4 for the futures and the spot markets respectively to get (3b). This is done by extracting the conditional variances from the equations for Tables 3 and 4 and assuming that the correlation between S and F is constant over time. The results for both conditional variances are almost similar, with the sum of the ARCH and GARCH coefficients approximately equal to one (but slightly greater than one). This is the autoregressive root that governs the persistence of volatility shocks. In many applied settings, this root is very close to unity so that shocks die out rather slowly. From the results in Tables 3 and 4, last period's forecast variance dominates the persistence of the volatility. This indicates that the returns adjust more with respect to last period's forecast variance. Figures 1 and 2 show the conditional variances of the spot and the futures markets respectively. We indicate the dates in the graphs to show that high variances occur during the financial crisis which indicates unusual volatility in the markets.

We next show the results of the bivariate GARCH(1,1) model and specified in (4) in Table 5. Concentrating on the variance equations for the spot and the futures market, we generated the dynamic conditional variance for both markets. It is interesting to observe that all the coefficients for the variance and covariance equations are highly significant. This indicates that the volatility spillover does exist between the markets. This is consistent with findings by Ross (1989) and Bollerslev *et al.* (1992). Further, the persistence of volatility in spot and futures markets are 0.9067 and 0.8069 respectively.

The covariance equation gives a persistent volatility of 0.8016. This again is consistent with the persistence of volatility where the shocks die out rather slowly. However, the bivariate GARCH(1,1) does better and makes more sense empirically than the conventional model as the persistence of the volatility is less than one. Thus the results from the bivariate GARCH are more meaningful than the conventional model. The final step would be to look at the variance of the portfolio (Equation 3b). We would expect the variance of the portfolio to be close to zero if hedging is to be effective. Figure 3 shows that the optimal

Table 2. Conventional GARCH(1,1) for $S_t = \alpha_0 + \beta F_t + \varepsilon_t$ (1996 – 2000)

	Coefficient	Std. error	z-statistic	Prob.
β	0.730192	0.009152	79.78083	0.0000
α_0	-7.46E-05	0.000162	-0.460212	0.6454
	Variance equation			
C	4.48E-07	1.46E-07	3.074276	0.0021
ARCH(1)	0.117743	0.013029	9.036928	0.0000
GARCH(1)	0.886628	0.011894	74.54145	0.0000

Table 3. Conventional GARCH(1,1) for $F_t = \gamma_0 + \gamma_1 F_{t-1} + \varepsilon_t$ (1996 – 2000)

	Coefficient	Std. error	z-statistic	Prob.
γ_0	0.000289	0.000398	0.726863	0.4673
γ_1	0.002570	0.032957	0.077986	0.9378
	Variance equation			
C	1.87E-06	6.07E-07	3.075500	0.0021
ARCH(1)	0.132811	0.011278	11.77619	0.0000
GARCH(1)	0.881087	0.007185	122.6208	0.0000

Table 4. Conventional GARCH(1,1) for $S_t = \gamma_0 + \gamma_1 S_{t-1} + \varepsilon_t$ (1996 – 2000)

	Coefficient	Std. error	z-statistic	Prob.
γ_0	0.000520	0.000371	1.400631	0.1613
γ_1	0.139781	0.032275	4.330994	0.0000
	Variance equation			
C	3.09E-06	6.16E-07	5.017229	0.0000
ARCH(1)	0.162365	0.016241	9.997128	0.0000
GARCH(1)	0.849446	0.012243	69.38051	0.0000

hedge ratio for the two GARCH models (noting that we have assumed the hedge ratio for the conventional method to be constant at 0.730192). The bivariate GARCH model, by construction, is able to capture the dynamic hedge ratio in the portfolio. This hedge ratio indicates the obvious fact that it is not constant due to the spillover effect between the two markets. It also indicates that the volatility of the spot and the futures markets are not the same over time. Thus hedgers need to constantly adjust their composition of spot and futures assets in their portfolio. For comparison purposes, we apply a similar bivariate

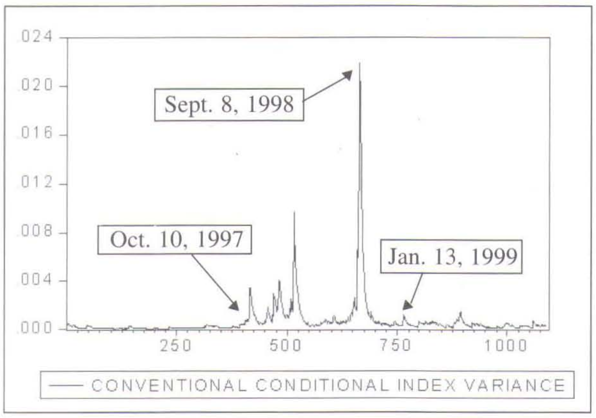

Figure 1. Conventional conditional variance of index return (1996 – 2000)

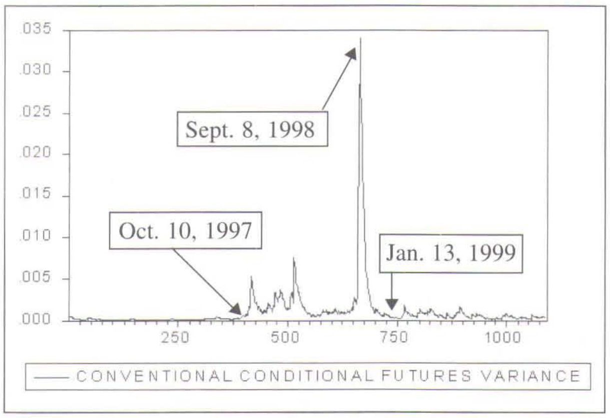

Figure 2. Conventional conditional variance of futures return (1996 – 2000)

GARCH model on data spanning 2004-2008, which is less volatile compared to 1996-2000. The results for the 2004-2008 data are shown in Figure 4. It can be seen that the need to adjust the hedge ratio is less during the period of less volatile. The difference between the variance of the bivariate and the conventional GARCH portfolios is given in Figure 5.

From Figure 3, it appears that the bivariate GARCH model is able to capture the spillover effect of the volatility better. Around June 1997, we observe that the hedge ratio from the bivariate model is starting to show the persistence in volatility, and this is captured by the parameters in the variance equations. Following the argument by Bollerslev (1986), we see that the conventional GARCH model understates the spillover effects between the spot and futures markets. Figure 5 shows that the difference between the portfolio variances is not very significant during the period of tranquility. However, during a period of financial crisis and high volatility in the market returns, the difference in the variance is relatively large. This indicates that the conventional method of calculating the portfolio variance fails to do the very job at the very time it is supposed to do for effective hedging of the spot

Table 5: Results from the bivariate GARCH(1,1) equation (4) (1996 – 2000)

Variable	Coeff.	Std. Error	t-Stat	Signif.
α_{11}	4.08E-04	4.63E-04	0.88113	0.3782
α_{12}	0.2175	0.0519	4.18825	0.0000
α_{13}	-0.0589	0.042	-1.40183	0.1610
α_{21}	5.56E-04	5.93E-04	0.93789	0.3483
α_{22}	0.4204	0.0659	6.37633	0.0000
α_{23}	-0.4132	0.0565	-7.31339	0.0000
β_{11}	1.06E-04	4.20E-06	25.31184	0.0000
β_{21}	1.42E-04	8.18E-06	17.39242	0.0000
β_{31}	1.77E-04	1.13E-05	15.7636	0.0000
β_{12}	0.4374	0.0125	34.99825	0.0000
β_{32}	0.4231	0.028	15.0921	0.0000
β_{22}	0.4684	0.0332	14.12715	0.0000
β_{13}	0.4693	0.032	14.68877	0.0000
β_{33}	0.3838	0.0319	12.02041	0.0000
β_{23}	0.3332	0.0392	8.50679	0.0000

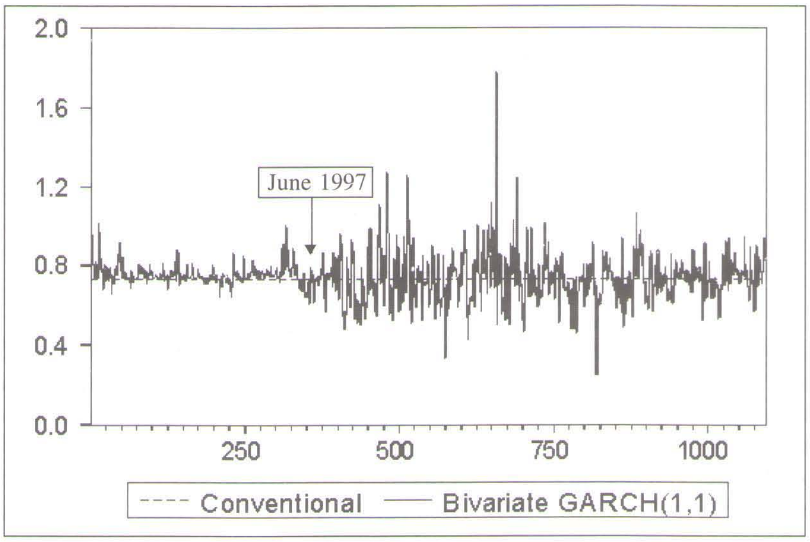

Figure 3. Hedging ratios (b) for conventional GARCH(1,1) and bivariate GARCH(1,1) (1996 – 2000)

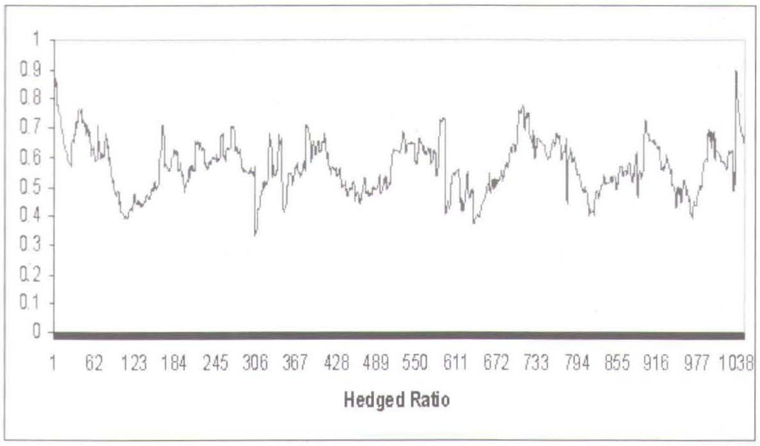

Figure 4. Hedging ratios (b) for bivariate GARCH(1,1) (2004 – 2008)

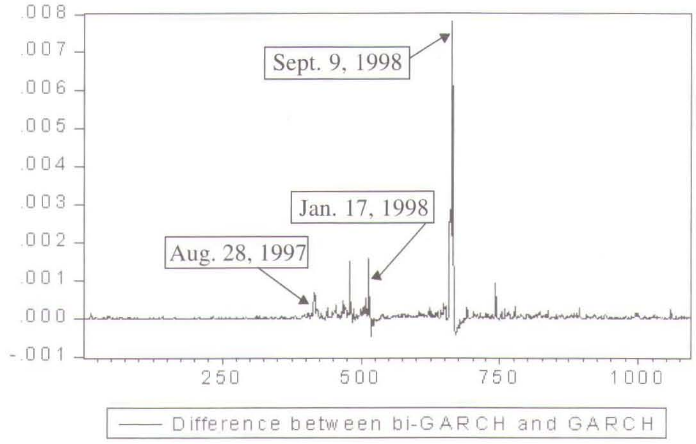

Figure 5. The difference in portfolio variance for bivariate GARCH and conventional GARCH (1996 – 2000)

market. The implications of these results are very important to hedgers. These include the optimal hedge ratio and the risk involved in hedging itself especially during the period of financial crisis.

5. Conclusion

This article investigates the effectiveness of hedging the cash markets index on the KLSE using the futures index on the MDEX. By application of the bivariate GARCH(1, 1) model, the time varying hedge ratio is able to capture the volatility spillover between the two markets. The model is more robust than the conventional GARCH model as it is able to incorporate the volatility simultaneously in the variance-covariance equations. The results indicate that the two models show an obvious disparity in the variance of the hedged portfolio when the economy was in the 1997 financial crisis. Using the bivariate GARCH, the variance of the portfolio is much larger than the conventional GARCH methodology, thus it underestimates the risk involved during the financial crisis. Further the results show that the persistence of shocks in the bivariate GARCH model is more stable and seems to die out slowly. The implication to investors is that it is still too risky to enter the market even with a hedged portfolio.

It is also found that a two-way relationship exists not only in the return of the cash and the futures markets, but also in the volatility of the returns. This supports that there is flow of information between the two markets with each market adjusting to any information from the other.

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