Wei-His Hsu (Taiwan), Yung-Shi Liau (Taiwan), Jack J.W. Yang (Taiwan)

Evaluating hedge ratios in the subprime mortgage crisis

Abstract

This paper employs the dynamic conditional correlation model of Engle (2002) with error correction terms to examine the hedge ratios of American (S&P 500 index), British (FTSE 100 index), Canadian (Toronto 60 index) and French (CAC 40 index) stock futures markets. We examined the variance of hedge ratios during the period of 2006-2008. Furthermore, since the serious subprime mortgage crisis began in June 2007 when two Bear Stearns hedge funds collapsed, we wanted to investigate two types of hedge ratios – the hedge ratio before June 2007 and the hedge ratio after June 2007. It is shown that the serious subprime mortgage crisis has led to a greater average hedge ratio of American, British, Canadian and French markets so far. This result is consistent with the findings of Lien (2005). In other words, the investors are inclined to weigh adverse evidence more heavily when they are in the asymmetry return of the financial assets. This finding is helpful to risk managers dealing with stock index futures in futures markets of USA, Britain, Canada and France.

Keywords: hedge ratios, subprime mortgage crisis, DCC-GARCH, ECM.
JEL Classification: G01, G14, G15, A11.

Introduction

The main objective for hedging is to minimize the variability of return on investment. In other words, hedging employs long-short strategies to reduce the variance of risk at the same time. One example is when an investor holds stocks he can adopt a short position on futures to offset risk. Hence, the measure of adopting a long-short position is defined as the hedge ratio, which represents the investor's attitude for future risk. Generally speaking, when the market trend is stable, the hedge ratio will get smaller, whereas if a big fluctuation of the market takes place it will get bigger.

Formerly, research about hedge ratios has overemphasized looking for the best value or comparing the models of the hedge ratio. For example, Park and Switzer (1995) estimated the risk-minimizing futures hedge ratio for three types of stock index futures: (i) S&P 500 index futures, (ii) major market index (MMI) futures, and (iii) Toronto 35 index futures, and the results reveal that the hedge ratio, which is estimated by Bivariate cointegration GARCH, is superior to the conventional ordinary least square (OLS) and OLS with cointegration (OLS-CI). Lien et al. (2002) compared OLS and constant-correlation vector generalized autoregressive conditional heteroscedasticity (VGARCH) and claimed that the OLS hedge ratio performs better than the VGARCH one. Floros and Vougas (2006) measured the hedging effectiveness of the Greek stock index futures using four different methods: (i) OLS, (ii) error correction model (ECM), (iii) vector error correction model (VECM), and (iv) Bivariate cointegration GARCH (B-GARCH). They found that the hedge ratio from the B-GARCH model provides greater variance reduction. This result is in accordance with Park and Switzer (1995). Hsu Ku et al. (2007) applied the dynamic conditional correlation (DCC)-GARCH model of Engle (2002) with error correction terms to investigate the optimal hedge ratios of British and Japanese currency futures markets and compare the DCC-GARCH and OLS model. Results show that the dynamic conditional correlation model yields the best hedging performance. The foregoing research overemphasizes looking for the best value or comparing the models of the hedge ratio. Research on how the positive and negative news affects the hedge ratio has seldom been conducted, especially when the market meets strong fluctuations.

The main reason why the financial assets generate asymmetric fluctuation is the investors' stronger reaction to negative news than to positive news. Recent research about the asymmetric fluctuation of the financial assets has been too numerous to enumerate (Blasco et al., 2002; You and Yang, 2003; Balaban and Bayar, 2005; Kian and Kuan, 2006; Jarkko Peltomaki, 2007; Liau and Yang, 2008). Moreover, the hedge ratio also generates variability following the asymmetric fluctuation of the financial assets. Brooks et al. employed the FTSE100 stock index to consider the impact of asymmetry on time-varying hedges and claimed that the asymmetric model gives superior hedging performance. Lien and Yang (2007) researched ten commodity futures contracts and estimated the dynamic minimum variance hedge ratios (MVHRs) using the Bivariate GARCH model that incorporates the basis spread effect of the asymmetric fluctuation. The results show that the positive basis spread has greater impact than the negative basis spread on the variance and covariance structure and they reported the importance of the asymmetric effect when estimating hedging strategies. Lee (2008) investigated the effects of asymmetries and regime switching on the futures hedging effectiveness of the Nikkei 225 stock index futures by using an asymmetric Markov regime switching BEKK GARCH (ARSBEKK) model. The results show that when the model takes the asymmetric effect into consideration, the hedging effectiveness is improved in estimating the hedge ratio, so the hedge ratio is in connection with the asymmetric fluctuation of the financial assets. Moreover, Lien (2005) incorporates asymmetric responses to positive and negative news within a stochastic volatility framework and the result shows that asymmetry leads to a greater average optimal hedge ratio. In other words, the hedge ratio increases with the increasing degree of asymmetry.

The global financial crisis that began in 2007 still continues. The U.S. "subprime mortgage crisis" has become a headline. Shah (2008) shows that the global financial crisis really started to show its effect in mid-2007 when two Bear Stearns hedge funds collapsed (see the *Economic Times*, 2008 12, 21) and in 2008 when stock markets around the world have fallen, large financial institutions have collapsed or been bought out (see http://www.globalissues.org). In this background, the returns of financial markets fluctuate widely and it is also worth to analyze the hedging effectiveness in various markets. Hence, this paper investigates two types of hedge ratios − the hedge ratio before June of 2007 and the hedge ratio after June of 2007 in the USA (S&P 500 index), Britain (FTSE 100 index), Canada (Toronto 60 index) and France (CAC 40 index). We want to investigate whether the U.S. subprime mortgage crisis leads to a greater average optimal hedge ratios in these four futures markets. The empirical results show that the average hedge ratios certainly have gone higher. In other words, investors are inclined to weigh adverse evidence more heavily when financial fluctuation increases. The result is consistent with the Lien's (2005) empirical finding.

This article is organized as follows. Section 1 reports the time series data and some descriptive statistics. Section 2 provides the DCC-GARCH with ECM and its specification for our empirical studies. Section 3 includes model estimations and the results of hedging effectiveness for the markets of the USA, Britain, Canada and France. Finally, the last section concludes with a discussion on the findings.

1. Data and descriptive statistics

The data employed in this paper are obtained from Datastream and the study period is from January 5, 2006 to December 31, 2008. The index price is defined as daily spot closing and futures settlement data for each market respectively. The index returns are defined as the natural logarithms difference of the index. Table 1 lists the descriptive statistics and unit-root test for the daily index returns of each market. The mean returns for each market are negative, and the skewness statistics show that all return series are either positively or negatively skewed. The kurtosis statistics show a departure from normality and all series are highly leptokurtic.

The Jargue-Bera (JB) statistics reject the normality for each return series. All these characters imply non-normal distributions with fatter tails. The Ljung-Box (LB) for the standardized squared residuals shows a serial correlations of second moments for both the spot and futures in all the markets. Therefore, it is appropriate to apply a GARCH model. Secondly, the results of the augmented Dickey-Fuller (ADF) test for the existence of a unit root are strongly rejected for log differences of both spot and futures prices, but cannot be rejected for the log level.

Table 1. Descriptive statistics and unit-root test

Market	Category	Mean	SD	Skew-ness	Kurtosis	Jarque-Bera	Q(8)	Q^2 (8)	Augmented Dickey-Fuller unit root test	
									Price	Return
USA	Spot	-0.0004	0.0162	-0.2848	14.2679	4128.7960***	60.7631	600.5211***	0.4002	-25.0403***
	Futures	-0.0005	0.0165	0.1030	17.7549	7076.8523***	55.3453	505.4467***	0.3555	-25.0728***
Britain	Spot	-0.0003	0.0155	-0.7085	11.5063	2352.0175***	57.2757	472.7727***	-0.7733	-13.7610***
	Futures	-0.0003	0.0154	-0.7369	11.5431	2376.3393***	53.9027	513.7381***	-0.9588	-13.8994***
Canada	Spot	-0.0002	0.0166	-0.0572	12.5484	3028.3146***	67.2153	708.6420***	-0.9011	-13.1110***
	Futures	-0.0002	0.0165	-0.1828	12.5483	3021.2507***	50.3011	635.3084***	-0.8874	-22.9893***
France	Spot	-0.0005	0.0161	0.1455	12.2283	2770.4861***	48.8558	384.1435***	0.0794	-13.8227***
	Futures	-0.0005	0.0164	-0.1298	11.1367	2153.8585***	39.7024	495.1756***	0.0931	-14.4136***

Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Q (8) and Q^2 (8) are the LB tests for the 8th-order serial correlations of standardized residuals and standardized squared residuals, respectively.

2. Model specifications

Several studies have probed the optimal hedge ratio for stock market portfolios using stock index futures, while restricting the hedge ratio to be constant over time. Engle (1982) and Bollersley (1986) estimated the optimal hedge ratio by modeling the distribution of stock index and futures changes within the generalized autoregressive conditional heteroscedasticity (GARCH). Park and Switzer (1995) claim that if the joint distribution of stock index and futures prices is changing over time, estimating a constant hedge ratio may not be appropriate.Higgs and Worthington (2004) capture the time-varying second moments of the joint distribution and use an error correction model (ECM) when co-integration occurs between financial variables. Floros and Vougas (2006) claim the M-GARCH model provides greater variance reduction. In other words, more recent papers use a variety of advanced econometric methods (i.e., ECM, VECM or M-GARCH) with or without error correction terms to estimate the optimal hedge ratios. Especially, Hsu Ku et al. (2007) conclude that the inclusion of dynamic conditional correlations (DCC) in the GARCH model can better capture the frequent fluctuations in futures markets. Thus, in order to account for the long-run stochastic trend, they incorporate a bivariate ECM in the Engle's (2002) DCC-GARCH. In this study, we incorporate a bivariate ECM in a DCC-GARCH model to estimate the hedge ratios.

In this article, we use the idea of DDC-GARCH with ECM which is specified and developed by Hsu Ku et al. (2007) to estimate hedge ratios. Given the dynamic conditional correlation (DDC) model, the GARCH specification requires modeling the first two conditional moments of the bivariate distributions of s_t and f_t. In order to account for the long-run stochastic common trend shared between the spot and futures market, the first moment can be modeled with a bivariate error correction model. In order to capture the time-varying variance and covariance, the second moment can be parameterized with a bivariate constant correlation GARCH (1,1) model. The bivariate distributions of spot and futures are assumed as follows:

$$s_t = \alpha_{0s} + \alpha_{1s}(S_{t-1} - \lambda F_{t-1}) + \varepsilon_{st}, \qquad (1)$$

$$f_t = \alpha_{0f} + \alpha_{1f}(S_{t-1} - \lambda F_{t-1}) + \varepsilon_{ft}, \qquad (2)$$

$$\begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Big/ \Psi_{t-1} \sim N(0, H_t), \qquad (3)$$

$$H_t = \begin{bmatrix} h_{s,t} & h_{sf,t} \\ h_{sf,t} & h_{f,t} \end{bmatrix}, \qquad (4)$$

$$h_{s,t} = v_{0s} + v_{1s}\varepsilon^2_{s,t-1} + v_{2s}h_{s,t-1}, \qquad (5)$$

$$h_{f,t} = v_{0f} + v_{1f}\varepsilon^2_{f,t-1} + v_{2f}h_{f,t-1}, \qquad (6)$$

$$h_{sf,t} = \rho_{sf,t}\sqrt{h_{s,t}}\sqrt{h_{f,t}}, \qquad (7)$$

$$\rho_{sf,t} = \frac{q_{sf,t}}{\sqrt{q_{ss.t}q_{ff,t}}}, \qquad (8)$$

$$q_{sf,t} = \bar{\rho}_{sf} + v(z_{s,t-1}z_{f,t-1} - \bar{\rho}_{sf}) + \delta(q_{sf,t-1} - \bar{\rho}_{sf}). \qquad (9)$$

We define s_t and f_t as the change in the price of the spot and futures between time t and t+1, respectively; S_{t-1} and F_{t-1} are the log prices of the foreign currency in US dollars for immediate and future delivery, respectively; Ψ_{t-1} is the information set at time t-1; the constant λ that appears in equations (1) and (2) is called the cointergrating parameter that links the spot and futures prices together, so the term $S_{t-1} - \lambda F_{t-1}$ in equations (1) and (2) is the error correction term, which imposes the long-run relationship (cointegration) between the spot and futures prices into the short-run model. The parameter $\rho_{sf,t}$ in equations (7) and (8) is the dynamic conditional correlations between the spot and futures returns and must be estimated; H_t in equation (4) is the conditional variance matrix at time t; the terms ε_{st} and ε_{ft} in equations (1) and (2) are the error terms which are dependent on the information set Ψ_{t-1}; h_{st} and h_{ft} are conditional variance of spot and futures returns, respectively. Eventually, the conditional correlation $q_{sf,t}$ which was specified by Engle (2002), is employed in equation (9), where $\bar{\rho}_{sf}$, $z_{s,t} = \varepsilon_{st}/\sqrt{h_{s,t}}$ and $z_{f,t} = \varepsilon_{ft}/\sqrt{h_{f,t}}$ are the constant unconditional correlation between spot and futures markets and the standardized residuals of the spot returns and of futures returns, respectively (for details see Hsu Ku et al. (2007)). In order to estimate the DCC-GARCH framework, we can use the maximum likelihood method (MLE). By way of MLE, we can obtain the estimates of $\rho_{sf,t}$, $\sqrt{h_{s,t}}$ and $\sqrt{h_{f,t}}$, thereby obtaining the optimal hedge ratio $b^*_t = h_{sf,t}/h_{f,t} = \rho_{sf,t}\sqrt{h_{s,t}}/\sqrt{h_{f,t}}$. In this paper, all the above methods of estimating the hedge ratios are applied and their effectiveness is compared.

3. Model estimation and comparison among hedging markets

The DCC-GARCH with the ECM model developed by Hsu Ku et al. (2007) is employed to capture dynamic conditional correlations as well as the long-run shared trends between spot and futures exchange returns. Table 2 summarizes the results of the DCC-GARCH estimated for all spot and futures markets. According to Table 2, regarding the conditional variance, it is shown that estimations of all parameters are statistically significant, revealing the existence of GARCH and the time-varying hedge ratios. Estimations of all parameters in the conditional correlations are statistically significant except for the parameter δ for Canada. It is shown that the persistences of the conditional correlations are all significant between the spot and futures markets in all the countries under study, except for Canada. The results of the LB(8) and LB(8)^2 statistics show that all LB(8) and LB(8)^2 statistics for the standardized residuals and standardized squared residuals show no serial correlations between the spot and futures in the USA, Britain, Canada and France at the 5% level of significance. It is shown that the design of the DCC-GARCH model has dealt with the condition of the non-normal distributions with fatter tails. Thus, the results in Table 2 suggest that the DCC-GARCH model is appropriate. We employ $b_t^* = \rho_{sf,t}\sqrt{h_{s,t}} / \sqrt{h_{f,t}}$ to obtain optimal hedge ratios for the DCC-GARCH models, respectively, and then calculate the average of the hedge ratios in every market.

Table 2. The hedge ratio results of four markets: MLE of DCC-GARCH model

$$S_t = \alpha_{0s} + \alpha_{1s}(S_{t-1} - \lambda F_{t-1}) + \varepsilon_{st}$$

$$f_t = \alpha_{0f} + \alpha_{1f}(S_{t-1} - \lambda F_{t-1}) + \varepsilon_{ft} \qquad \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Big/ \Psi_{t-1} \sim N(0, H_t)$$

$$h_{s,t} = v_{0s} + v_{1s}\varepsilon^2_{s,t-1} + v_{2s}h_{s,t-1} \qquad H_t = \begin{bmatrix} h_{s,t} & h_{sf,t} \\ h_{sf,t} & h_{f,t} \end{bmatrix}$$

$$h_{f,t} = v_{0f} + v_{1f}\varepsilon^2_{f,t-1} + v_{2f}h_{f,t-1} \qquad \rho_{sf,t} = \frac{q_{sf,t}}{\sqrt{q_{ss,t}q_{ff,t}}}$$

$$h_{sf,t} = \rho_{sf,t}\sqrt{h_{s,t}}\sqrt{h_{f,t}} \qquad q_{sf,t} = \bar{\rho}_{sf} + v(z_{s,t-1}z_{f,t-1} - \bar{\rho}_{sf}) + \delta(q_{sf,t-1} - \bar{\rho}_{sf})$$

Parameter	USA	Britain	Canada	France
Conditional mean				
α_{0s}	4.92e-04 (16.721)***	5.26e-04 (1.714)*	4.20e-04 (1.131)	4.47e-04 (19.343)***
α_{1s}	-0.085 (16.721)***	-0.127 (-3.155)***	-0.107 (-2.967)***	-0.134 (-143.48)***
α_{0f}	4.43e-04 (30.757)***	5.00e-04 (1.654)*	3.96e-04 (1.208)	4.22e-04 (10.069)***
α_{1f}	-0.066 (-2.963)***	-0.106 (-2.678)***	-0.121 (-3.438)***	-0.136 (-47.910)***
Conditional variance				
v_{0s}	5.40e-06 (5.964)***	4.86e-06 (3.725)***	2.02e-06 (2.908)***	1.17e-05 (32.928)***
v_{1s}	6.61e-06 (8.326)***	0.188 (8.146)***	0.079 (7.109)***	0.246 (104.729)***
v_{2s}	0.850 (51.155)***	0.823 (44.737)***	0.909 (67.146)***	0.710 (70.741)***
v_{0f}	6.61e-06 (6.499)***	4.62e-06 (3.857)***	2.07e-06 (3.068)***	1.21e-05 (37.956)***
v_{1f}	0.142 (9.090)***	0.188 (7.934)***	0.073 (7.167)***	0.250 (21.139)***
v_{2f}	0.827 (46.615)***	0.826 (43.217)***	0.915 (74.224)***	0.702 (59.983)***
Conditional correlation				
γ	0.075 (87.196)***	0.076 (3.134)***	0.056 (2.306)***	0.126 (30.748)***
δ	-0.158 (-38.470)***	0.829 (13.687)***	0.016 (0.068)	-0.195 (-29.913)***

Table 2 (cont.). The hedge ratio results of four markets: MLE of DCC-GARCH model

LB tests for 8th-order serial correlation of standardized residuals and standardized squared residuals					
Parameter		USA	Britain	Canada	France
Spot	Q(8)	8.625	6.990	7.030	6.877
	Q^2 (8)	8.807	10.641	14.299*	13.662*
Futures	Q(8)	7.663	5.672	5.647	8.112
	Q^2 (8)	4.337	8.199	11.150	11.784

Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Q (8) and Q^2 (8) are the LB tests for the 8 th-order serial correlation of standardized residuals and standardized squared residuals, respectively. The parameters of γ and δ are the coefficients included in Equation 9. The regression DCC-GARCH model contains all Equations 1-9.

Table 3 presents the number, average, variance and t-value of the optimal hedge ratio in the USA, Canada, Britain and France. In every market, we divided the full period from January 2006 to December 2008 into two sub-periods in accordance with the serious subprime mortgage crisis which began when two Bear Stearns hedge funds collapsed. One sub-period is from January 2006 to June 2007, the other is from July 2007 to December 2008. In every market, for the sub-period of January 2006 to June 2007 we observed 387 samples to calculate the hedge ratios, and for the sub-period of July 2007 to December 2008 392 observed samples are used to calculate the hedge ratios. For the full period (January 2006 to December 2008) the average hedge ratio of 1.0067 for Britain was the highest hedge ratio in all the markets. And the average hedge ratios of 0.9919 for France and 0.9795 for the USA are the second and third high. The average hedge ratio 0.9525 for Canada is the lowest. In sum, Britain is the only market whose average hedge ratio is more than one. And the Canadian market belongs to the lower hedge ratio category. The remaining market such as the USA is in the middle hedge ratio category. With regard to the variance of the hedge ratio, the empirical results show that every market exhibits similar volatility in both sub-periods. But for the full period (January 2006 to December 2008), the variance of the hedge ratio was higher in the USA and lower in Canada. And the variance of the hedge ratio in both Britain and France were in the middle. Since this paper examines whether the hedge ratios have changed after the serious subprime mortgage crisis, Table 3 illustrates the hedge ratios comparison for the two sub-periods. In each market t-values are all significant at the 1% level. The results show that investors are more risk-averse during the serious subprime mortgage crisis. Moreover, this result is consistent with the empirical findings of Lien (2005).

Table 3. The number, average, variance and t-value of optimal hedge ratios in the USA, Britain, Canada and France

Market	Number of hedge ratios 2006/01~ 2007/06	Number of hedge ratios 2007/07~ 2008/12	Average of hedge ratio 2006/01~ 2008/12	Average of hedge ratio 2006/01~ 2007/06	Average of hedge ratio 2007/07~ 2008/12	Variance of hedge ratio 2006/01~ 2008/12	Variance of hedge ratio 2006/01~ 2007/06	Variance of hedge ratio 2007/07~ 2008/12	$H_0: \mu_1 = \mu_2$ $H1: \mu_1 \neq \mu_2$ t-value
USA	387	392	0.9795	0.9710	0.9878	0.0023	0.0015	0.0015	5.0130***
Britain	387	392	1.0067	1.0024	1.011	0.0019	0.0015	0.0015	2.7141***
Canada	387	392	0.9525	0.9430	0.9618	0.0016	0.0015	0.0015	6.6930***
France	387	392	0.9919	0.9872	0.9966	0.0019	0.0014	0.0014	3.0201***

Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. μ_1 is the average hedge ratio from January 2006 to June 2007 and μ_2 is the average hedge ratio from July 2007 to December 2008.

Figures 1-4 display the time-varying hedge ratio for each market over the two sub-periods (i.e. the period before and after the serious subprime mortgage crisis began). Though the hedge ratio of Britain has a dropping tendency after June 2008, the hedge ratio has a rising tendency in all four markets when the serious subprime mortgage crisis began. The condition is consistent with the results in Table 3.

More specifically, our results present at least three important implications for financial market investors who want to reduce portfolio risk using futures contracts. First, it is shown that when the investment market is characterized by the asymmetry return of the financial assets, especially in the U.S. "subprime mortgage crisis", the decision makers not only generate strong reflections but also are inclined to weigh adverse evidence more heavily. Secondly, the hedge ratio is in accordance with asymmetric volatility of the risk, so the hedge ratio has an impact on the decision making of the investors.

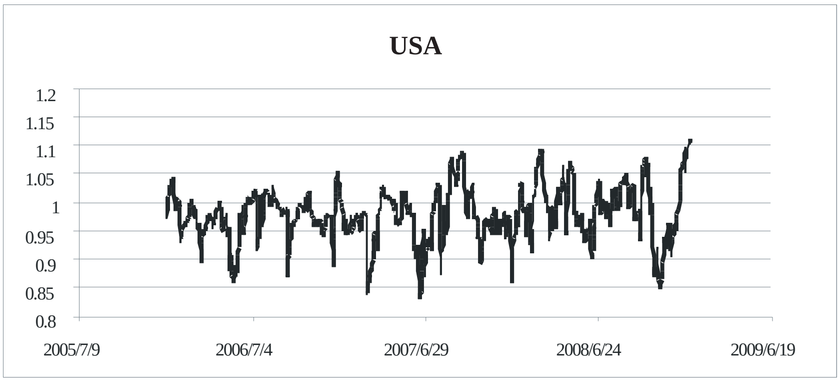

Fig. 1. Time-varying hedge ratio in DCC-GARCH with ECM estimations for USA

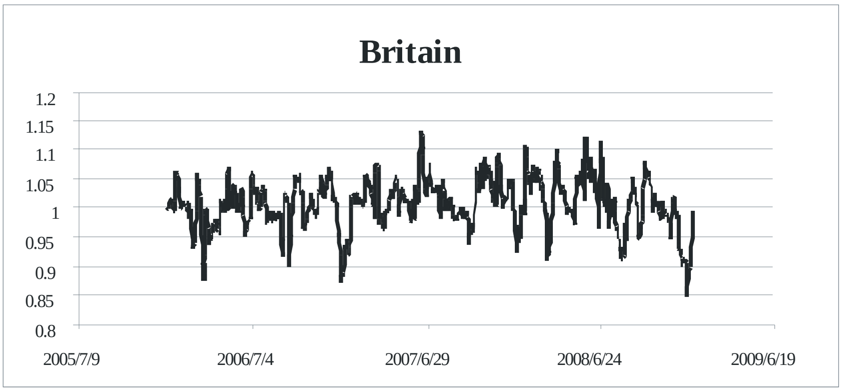

Fig. 2. Time-varying hedge ratio in DCC-GARCH with ECM estimations for Britain

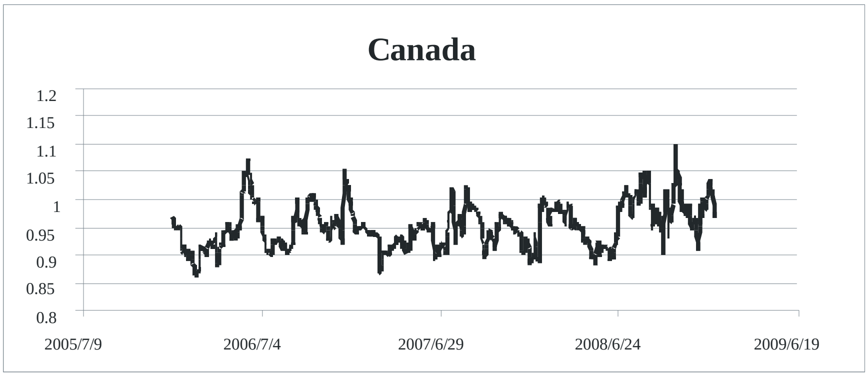

Fig. 3. Time-varying hedge ratio in DCC-GARCH with ECM estimations for Canada

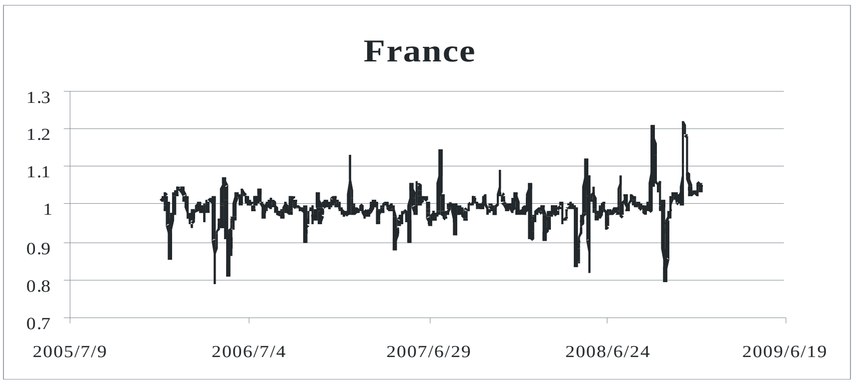

Fig. 4. Time-varying hedge ratio in DCC-GARCH with ECM estimations for France

Thirdly, with regard to the risk arbitrage, the main goal of hedging is to minimize the variability of return on investment. When the financial crisis happens the hedge ratios are expected, in general, to get bigger. The investors can employ the hedge ratios (the measure of adopting a long-short position) to reduce the variance of risk and make profit.

Conclusions

This paper investigates the hedge ratio change of American, British, Canadian and French markets using the DCC-GARCH of Chen et al. (2007) with error correction terms. It is shown that the serious subprime mortgage crisis has led to a greater average hedge ratio. The empirical results show that investors are more conservative during the time the serious subprime mortgage crisis begins. In other words, it is shown that when the investors are in the asymmetry return of the financial assets, especially in the U.S. "subprime mortgage crisis", the decision makers not only generate strong reflections but also are inclined to weigh adverse evidence more heavily. This result is consistent with the empirical findings of Lien (2005).

While the major purposes of this paper have been fulfilled, further research problems remain unsolved. For instance, future research could use different markets, data frequencies and time-periods to explore the changing hedge ratios.

References

1. Balaban, E. and Bayar, A. (2005), "Stock return and volatility: empirical evidence from fourteen countries", Applied Economics Letters, 12: 603-611.
2. Blasco, N., Corredor, P. and Santamaria, R. (2002), "Is bad news cause of asymmetric volatility response? A note," Applied Economics, 34: 1227-1231.
3. Brooks, C., Henry, O.T. and Persand, G. (2002), "The effect of asymmetries on optimal hedge ratios", Journal of Business, 75 (2).
4. Engle, R.F. (1982), "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation", Econometrica, 50: 987-1007.
5. Engle, R.F. (2002), "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models", Journal of Business and Economic Statistics, 20(3): 339-350.
6. Engle, R.F. and Granger, C.W.J. (1987), "Co-integration and error correction: representation, estimation and testing", Econometrica, 55(2), March: 251-276.
7. Engle, R.F. and Kroner, K.F. (1995), "Multivariate simultaneous generalized ARCH, Econometric Theory", 11(1), Mar: 122-150.
8. Floros, C. and Vougas, D.V. (2006), "Hedging effectiveness in Greek Stock Index Futures Market, 1999-2001", International Research Journal of Finance and Economics, 5: 1450-2887.
9. Higgs, H. and Worthington, A.C. (2004), "Transmission of returns and volatility in art markets: a multivariate GARCH analysis", Applied Economics Letters, 11(4): 217-222.
10. Hsu Ku, Y.H., Chen, Ho. C. and Chen, K.H. (2007), "On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios", Applied Economics Letters, 14: 503-509.
11. Kian, T.K. and Kuan, N.K. (2006), "Exchange rate volatility and volatility asymmetries: an application to finding a natural dollar currency", Applied Economics, 38: 307-23.
12. Lee, H.T. (2008), "The effects of asymmetries and regime switching on optimal futures hedging", Applied Financial Economics Letters, 4: 133-136.
13. Liau, Y.S. and Yang, J.J.W. (2008), "The mean/volatility asymmetry in Asian stock markets", Applied Financial Economics, 18(5): 411-419.
14. Lien, D. and Li Y. (2007), "Asymmetric effect of basis on dynamic futures hedging: empirical evidence from commodity markets", Journal of Banking & Finance, 32: 187-198.
15. Line, D., Tse, Y.K. and Tsui, A.K.C. (2002), "Evaluating the hedging performance of the constant-correlation GARCH model", Applied Financial Economics, 12: 791-798.
16. Line, D., (2005), "A note on asymmetric stochastic volatility and futures hedging", The Journal of Futures Markets, 25(6): 607-612.
17. Park, T.H. and Switzer, L.N. (1995), "Time-varying distributions and the optimal hedge ratios for stock index futures", Applied Financial Economics, 5: 131-137.
18. Yang, J.J.W. and You, S.J. (2003), "Asymmetric volatility: pre and post financial crisis", Journal of Management, 20: 797-819.