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Full Length Research Paper

Asymmetric dynamic hedging effectiveness: Evidence from Taiwan Stock Index Futures

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This study examines the asymmetric dynamic hedging effectiveness the Taiwan stock index futures by extending the concepts of naive hedging effectiveness and dynamic hedging effectiveness proposed by Choudhry (2003). Based on the minimum-variance hedging portfolio, static hedging models and dynamic hedging models are also compared in terms of hedging effectiveness, dynamic hedging effectiveness, hedging effectiveness of dynamic conditional correlation and asymmetric dynamic hedging effectiveness. Experimental results indicate that, there is an asymmetric dynamic hedging effectiveness in the Taiwan stock index futures asymmetric dynamic hedging. Additionally, hedging effectiveness of the dynamic conditional correlation hedging model is better than that of the conditional correlation hedging model. We thus recommend that investors consider the asymmetric dynamic hedging model when constructing the minimum-variance hedging portfolio.

Key words: Futures, hedging, hedging effectiveness, asymmetric dynamic hedging effectiveness.

INTRODUCTION

Global stock markets have undergone dramatic changes in recent decades. Risk management has become increasingly important in the future as investors recognize their exposure to a greater degree of uncertainty in stock markets. Among the many hedging strategies designed for investors include financial derivatives, especially stock index futures. Since financial derivatives are derived from their underlying spot assets, the appropriate hedging strategies may result in a satisfactory hedging performance, especially when the corresponding assets are closely related to each other.

The Taiwan futures exchange (TAIFEX) introduced Taiwan stock exchange capitalization weighted stock index (TAIEX) futures in 1998. Despite the global financial crisis in 2008, the futures market in Taiwan continues to perform well, as evidenced by an annual trading volume of 37,724,589 contracts, representing a growth rate of 122.07% over the previous year. Additionally, the growth rate of trading volume for the Taiwan futures markets is 14.9% higher than that of trading volume of global futures markets. In 2009, the trading volume of the Taiwan futures market was 44,886,570 contracts, that is, an increase of 18.98% over the previous year, despite the fact that the global futures market decreased by 1.7% during the same period. Additionally, whereas trade barriers that limited the extent of price change, foreign ownership, and margin trading impeded the Taiwan stock market previously, the gradual lifting of these market barriers via the Taiwanese government's policy of financial liberalization has led to more active trading in the Taiwan stock and futures markets. This example provides a valuable reference for emerging markets.

Ederington (1979) classified hedging theory into three types based on hedging purpose and motivation. First, the naïve hedging theory assumes that the change

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directions and volatility of the spot price are the same as those for the futures price, and hedgers in the spot market take opposite exposures. However, risk cannot be eliminated completely because the volatilities of both spot and futures prices are not entirely consistent with each other; in contrast, that theoretical assumption has been proven empirically to be incorrect. Second, the Working hypothesis hedge theory developed by Working (1953), also referred to as the selective hedging theory or expected profit maximization, posits that investors hedge their risks when basic changes are expected.

Finally, the portfolio hedge theory, as developed by Ederington (1979) in response to Johnson's (1960) conclusion that hedgers should regard spot and futures positions as a portfolio, seeks only risk minimization and uses the optimal hedging ratio to offset the potential losses incurred from the spot market, a situation referred to as minimum- variance hedging. Consequently, exactly how many futures positions investors should use hedging and selection of an optimal hedging ratio has received considerable interest. Most studies adopt the ordinary least squares (OLS) model to estimate the optimal hedging ratio, a model referred to as static hedging. Notable examples include Kroner and Sultan (1993), Lien and Yang (2004), and Yang and Lai (2009). However, a naive OLS model does not consider whether a variable has a serial correlation or heterogeneity in variance, causing the static hedging ratio to ignore a situation in which asset risk fluctuates with the arrival of new information.

As volatility clustering always occurs in financial data, time-variant volatility is often identified using GARCH-family models. Notable examples include the autoregressive conditional heteroskedasticity (ARCH) model developed by Engle (1982) and the generalized autoregressive conditional heteroskedasticity (GARCH) model developed by Bollerslev (1986). However, while unable to detect good and bad news, the GARCH model may have different predictive powers for the volatility of the asset prices. Bad news triggering a larger volatility than good news does explains why volatility is underestimated for bad news and overestimated for good news in a volatility model that ignores asymmetric effects, leading to an inaccurate prediction of volatility. Black (1976), Nelson (1990), Chang and Goo (2003), and Hodgson et al. (2006) found asymmetric effects in the stock market. Notably, a dynamic hedging model normally examines hedging effectiveness by utilizing a GARCH-family model. Additionally, the hedging effectiveness of a dynamic hedging model is better than that of static hedging models (Kroner and Sultan, 1993; Park and Switzer, 1995; Holmes, 1996; Tong, 1996; Choudhry, 2004; Lee and Yoder, 2007a and 2007b; Switzer and El-Khoury, 2007; Kavussanos and Visvikis, 2008; Andani et al., 2009; Yang and Lai, 2009; Park and Jei, 2010). In contrast, the asymmetric hedging effectiveness of symmetric dynamic hedging models has seldom been addressed.

Based on the minimum-variance hedging portfolio, the static hedging models and dynamic hedging models are also compared in terms of hedging effectiveness, dynamic hedging effectiveness, hedging effectiveness of dynamic conditional correlation, and asymmetric dynamic hedging effectiveness. This comparison is made among the following hedging models: the static hedging models (naive hedging model and naive OLS model) and dynamic hedging models (vector error correct multivariate GARCH model with a constant conditional correlation, vector error correct multivariate GJR-GARCH model with a constant conditional correlation, vector error correct multivariate GARCH model with a dynamic conditional correlation, and vector error correct multivariate GJR-GARCH model with a dynamic conditional correlation).

According to empirical findings, comparing various hedging models in terms of hedging effectiveness, based on the minimum-variance hedging portfolio, reveals that the hedging effectiveness of the naive hedging model in the static hedging models, 0.80404, is the lowest among all of the models. This finding suggests that in the static hedging models, hedging effectiveness of the naive hedging model is at least 80.404%. In dynamic hedging models, hedging effectiveness of the VEC-MGARCH-t model with a constant conditional correlation is the lowest among all of the models. We can thus infer that hedging effectiveness in the dynamic hedging models is at least 85.685%.

Comparing the dynamic conditional correlation hedging models with the constant conditional correlation hedging models reveals that the former has a higher hedging effectiveness than the latter. Importantly, this study demonstrates that the asymmetric dynamic hedging models have a higher hedging effectiveness than the symmetric dynamic hedging models, suggesting that there is an asymmetric dynamic hedging effectiveness in the Taiwan stock index futures. The rest of this paper is organized as follows. Section 2 describes the sample selection and methodology. Section 3 then summarizes the empirical results. Conclusions are finally drawn in Section 4, along with recommendations for future research.

METHODOLOGY

Sample selection

The sample period lasted from July 21, 1998 to October 29, 2010. Data regarding the Taiwan weighted stock index and index futures was obtained from the Taiwan Economic Journal Database (TEJ). In total, 3,101 sample observations were made. Daily index stock returns and index stock futures returns were calculated as the difference in the natural logarithms of daily closing prices, and then multiplied by 100.

This study adopts the window-rolling method to ensure that the daily hedge ratio and hedging effectiveness are adjusted according to the latest information. Generally, using out-of-sample forecasts to calculate the hedging effectiveness is a more precise means than using in-sample (Baillie and Myers, 1991; Brenner et al., 1996; Lee and Hung, 2007; Park and Jei, 2010; Lai and Sheu, 2010). Additionally, Choudhry (2009) suggested that one year and two year forecast horizons do not differ from each other. This study calculates the hedging effectiveness using out-of-sample forecasts for one year. Thus, 250 sample observations were made during the test period.

Empirical models

Vector Error Correct Multivariate GARCH (VEC-MGARCH) Model with a constant conditional correlation

Chan et al. (1991) developed a bivariate GARCH model with a constant conditional correlation. An error correction term is added in the mean equation and vector error correct multivariate GARCH (VEC-MGARCH) model, with the constant conditional correlation specified as follows:

$$\boldsymbol{r}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{r}_{t-1} + \boldsymbol{\tau}\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right) + \boldsymbol{\varepsilon}_t, \quad (1)$$

$$vech(\Sigma_t) = vech(\boldsymbol{A}_0) + \sum_{i=1}^{m} \boldsymbol{A}_i vech\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \sum_{j=1}^{s} \boldsymbol{B}_j vech\left(\Sigma_{t-j}\right), \quad (2)$$

$$\sigma_{12,t}^2 = \rho_{12}\sigma_{11,t}\sigma_{22,t}, \quad (3)$$

$\boldsymbol{\tau} = [\tau_1 \quad \tau_2]'$, $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t} \quad \varepsilon_{2,t}]'$, $\boldsymbol{\tau}\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right)$ denotes the error correction term, $\boldsymbol{A}_0$ represents a (2×2) positive-definite and asymmetric matrix, $\boldsymbol{A}_i$ and $\boldsymbol{B}_j$ refer to a (3×3) matrix, $vech(\bullet)$ denotes the operation factor of a (3×1) vector that is stacked from a (2×2) matrix of lower triangular form, and $\sigma_{12,t}^2$ represents the covariance of stock index and stock index futures at time *t.*

Vector Error Correct Multivariate GJR-GARCH (VEC-GJR-MGARCH) Model with a constant conditional correlation

Femandez-Izquierdo and Lafuente (2004) developed a bivariate GJR-GARCH model with a constant conditional correlation. An error correction term is added in the mean equation and vector error correct multivariate GJR-GARCH (VEC-GJR- MGARCH) model with the constant conditional correlation specified as follows:

$$\boldsymbol{r}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{r}_{t-1} + \boldsymbol{\tau}\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right) + \boldsymbol{\varepsilon}_t, \quad (4)$$

$$vech(\Sigma_t) = vech(\boldsymbol{A}_0) + \sum_{i=1}^{m} \boldsymbol{A}_i vech\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \sum_{j=1}^{s} \boldsymbol{B}_j vech\left(\Sigma_{t-j}\right) + \boldsymbol{\gamma}\boldsymbol{I}_{t-1}\varepsilon_{t-1}^2, \quad (5)$$

Vector Error Correct Multivariate GARCH (VEC-MGARCH) Model with a dynamic conditional correlation

In an empirical study, the correlation coefficient tends to change over time. Therefore, in this study, the vector error correct

$$\sigma_{12,t}^2 = \rho_{12}\sigma_{11,t}\sigma_{22,t}, \quad (6)$$

where $\boldsymbol{\gamma} = [\gamma_1 \quad \gamma_2]'$, $\boldsymbol{I}_{t-1} = [I_{1,t-1} \quad I_{2,t-1}]'$.

Vector Error Correct Multivariate GARCH (VEC-MGARCH) Model with a dynamic conditional correlation

In an empirical study, the correlation coefficient tends to change over time. Therefore, in this study, the vector error correct multivariate GARCH model with a dynamic conditional correlation is based on the multivariate GARCH model with a dynamic conditional correlation proposed by Engle (2002). Therefore, an error correction term is added in the mean equation. The model is thus specified as follows:

$$\boldsymbol{r}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{r}_{t-1} + \boldsymbol{\tau}\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right) + \boldsymbol{\varepsilon}_t, \quad (7)$$

$$vech(\Sigma_t) = vech(\boldsymbol{A}_0) + \sum_{i=1}^{m} \boldsymbol{A}_i vech\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \sum_{j=1}^{s} \boldsymbol{B}_j vech\left(\Sigma_{t-j}\right), \quad (8)$$

$$\Sigma_t = \boldsymbol{D}_t^{1/2}\boldsymbol{\psi}_t\boldsymbol{D}_t^{1/2}, \quad (9)$$

$$\boldsymbol{\psi}_t = diag(Q_t)^{-1/2} \times Q_t \times diag(Q_t)^{-1/2}, \quad (10)$$

$$Q_t = (1-\delta_1-\delta_2)\overline{Q} + \delta_1\left(u_{t-1}u_{t-1}'\right) + \delta_2 Q_{t-1}, \quad (11)$$

where $\overline{Q}$ denotes the unconditional covariance matrix of $\boldsymbol{u}_t = \{\varepsilon_{1,t}/\sigma_{1,t}, \ \varepsilon_{2,t}/\sigma_{2,t}\}$ and $diag(Q_t)$ represents a diagonal matrix of Q_t.

Vector Error Correct Multivariate GJR-GARCH (VEC-GJR-MGARCH) Model with a dynamic conditional correlation

Regarding the price adjustment behavior of the GARCH model for financial assets, the returns volatility is generally assumed to have a symmetric effect. Because the explanatory ability and predictability in response to an actual situation might be inadequate, the model should include the asymmetry of returns volatility.

Therefore, in this study, the vector error correct multivariate GJR-GARCH model with a dynamic conditional correlation is based on a bivariate GJR-GARCH model with a dynamic conditional correlation proposed by Femandez-Izquierdo and Lafuente (2004). An error correction term and dynamic conditional correlation are thus incorporated in the model, which is specified as follows:

$$\boldsymbol{r}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{r}_{t-1} + \boldsymbol{\tau}\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right) + \boldsymbol{\varepsilon}_t, \quad (12)$$

$$vech\left(\Sigma_t\right) = vech\left(\boldsymbol{A}_0\right) + \sum_{i=1}^{m} \boldsymbol{A}_i vech\left(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'}\right) + \sum_{\boldsymbol{j=1}}^{\boldsymbol{s}} \boldsymbol{B_j} vech\left(\Sigma_{t-j}\right) + \boldsymbol{\gamma I}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{2}, \quad (13)$$

$$\Sigma_t = \boldsymbol{D}_t^{1/2}\boldsymbol{\psi}_t\boldsymbol{D}_t^{1/2}, \quad (14)$$

$$\boldsymbol{\psi_t} = diag\left(Q_t\right)^{-1/2} \times Q_t \times diag\left(Q_t\right)^{-1/2}, \quad (15)$$

$$Q_t = \left(1 - \delta_1 - \delta_2\right)\overline{Q} + \delta_1\left(u_{t-1}u_{t-1}^{'}\right) + \delta_2 Q_{t-1}. \quad (16)$$

Measurements of hedging effectiveness

Based on the minimum-variance hedging portfolio, this study investigates the hedging effectiveness, dynamic hedging effectiveness, hedging effectiveness of a dynamic conditional correlation, and asymmetric dynamic hedging effectiveness among various models, which include static hedging models (naive hedging model and naive OLS model) and dynamic hedging models (vector error correct multivariate GARCH model with a constant conditional correlation, vector error correct multivariate GJR-GARCH model with a constant conditional correlation, vector error correct multivariate GARCH model with a dynamic conditional correlation, and vector error correct multivariate GJR-GARCH model with a dynamic conditional correlation). Johnson (1960) developed both the minimum-variance portfolio hedge ratio and the optimal hedge ratio at time *t* as $\mathrm{cov}\left(r_t^s, r_t^f\right)/\mathrm{var}\left(r_t^f\right)$, where $\mathrm{cov}\left(r_t^s, r_t^f\right)$ denotes the covariance of stock index and stock index futures returns at time *t* and $\mathrm{var}\left(r_t^f\right)$ represents the variance of stock index futures returns at time *t*.

Hedging effectiveness

Johnson (1960) defined hedging effectiveness $\left(HE_T\right)$ as the percentage of reduction of the variance of hedge models in comparison with that of unhedged situations:

$$HE_T = \frac{\sigma_U^2 - \sigma_H^2}{\sigma_U^2}, \quad (17)$$

where σ_U^2 and σ_H^2 denote the variance of unhedged and hedged situations, respectively. While a larger HE_T implies a more effective hedge, while a smaller HE_T implies a less effective hedge.

Dynamic hedging effectiveness

Dynamic hedging effectiveness $\left(HE_D\right)$ denotes the percentage of reduction of the variance of the dynamic hedge models in comparison with that of static hedge models:

$$HE_D = \frac{\sigma_s^2 - \sigma_D^2}{\sigma_s^2}, \quad (18)$$

where σ_s^2 and σ_D^2 denote the variance of static and dynamic hedge models, respectively. A positive value of HE_D means that the hedge effectiveness of dynamic hedge models is better than that of static hedge models. Conversely, a negative value of HE_D means that the hedge effectiveness of the static hedge models is better than that of the dynamic hedge models.

Hedging effectiveness of dynamic conditional correlation

Dynamic conditional correlation hedging effectiveness $\left(HE_Y\right)$ represents the percentage of reduction in variance of the dynamic conditional correlation hedging models in comparison with constant conditional correlation hedging models:

$$HE_Y = \frac{\sigma_C^2 - \sigma_Y^2}{\sigma_C^2}, \quad (19)$$

where σ_C^2 and σ_Y^2 denote the variances of constant conditional correlation hedging models and dynamic conditional correlation hedging models, respectively. A positive value of HE_Y implies that dynamic conditional correlation hedging models are better than constant conditional correlation hedging models in terms of hedging effectiveness. Otherwise, dynamic conditional correlation hedging models are worse than constant conditional correlation hedging models in terms of hedging effectiveness.

Asymmetric dynamic hedging effectiveness

Asymmetric dynamic hedging effectiveness $\left(HE_A\right)$ is defined as the percentage of reduction of the variance of asymmetric dynamic hedge models compared with that of the symmetric dynamic hedge models:

$$HE_A = \frac{\sigma_S^2 - \sigma_A^2}{\sigma_S^2}, \quad (20)$$

where σ_S^2 and σ_A^2 denote the variance of symmetric dynamic hedge models and asymmetric dynamic hedge models, respectively. A positive value of HE_A implies that asymmetric dynamic models are better than symmetric dynamic models in terms of the hedging effectiveness. Conversely, a negative value of HE_A implies that asymmetric dynamic models are worse than the symmetric dynamic models in terms of hedging effectiveness.

Test for hedging effectiveness

Hedging effectiveness is defined as $\left(\sigma_i^2 - \sigma_j^2\right)/\sigma_i^2$, in which σ_i^2 and σ_j^2 are the variance of model i and j, respectively. As $\sigma_i^2 > \sigma_j^2$, that is, the value of hedging effectiveness is positive, the hedging effectiveness of model j is better than that of model i.Therefore, the null hypothesis H_0 and alternative hypothesis H_1, respectively, to test hedging effectiveness are:

$$H_0 : \sigma_i^2/\sigma_j^2 = 1 \ vs. \ H_1 : \sigma_i^2/\sigma_j^2 > 1.$$

$F = s_i^2/s_j^2 \sim F_{n_i, n_j}$ under null hypothesis is used to test various hedging effectiveness, a n_i denotes the degree of freedoms related to S_i^2 and n_j represents the degree of freedoms related to S_j^2. Given a significant level α, if test statistic $F = s_i^2/s_j^2 > F_{(n_i, n_j);\alpha}$, then reject H_0. Hence the variance of model i is larger than that of j.

RESULTS

Summary statistics and ARCH test

Table 1 summarizes the ARCH test analysis results. At 5% significant level, the means of the Taiwan stock index and stock index futures returns series are insignificantly different from 0 for the whole sample period and the estimation period other than the test period. The skewness values of the Taiwan stock index and stock index futures returns series significantly differ from 0 at 5% significant level for the whole sample period and the estimation period other than for the test period. The excess kurtosis values of the Taiwan stock index and stock index futures returns series are more than 3 at 5% significant level for all periods. Therefore, the Taiwan stock index and stock index futures returns series are leptokurtic forms. Based on the Jarque-Bera test, the Taiwan stock index and stock index futures returns series are not normally distributed for all periods. The Ljung-Box Q test for the lag-6 Taiwan stock index and futures returns series are statistically significant at 5% significant level for the whole sample period and the estimation period, suggesting a linear intertemporal dependence in the Taiwan stock index and stock index futures returns series. However, they are statistically insignificant for the test period, implying no linear intertemporal dependence in the Taiwan stock index and stock index futures returns series. Ljung-Box Q test for the lag-6 squared returns series of Taiwan stock index and stock index futures returns are statistically significant at 5% significant level for the whole sample period, estimation period, and test period, suggesting a linear intertemporal dependence in the squared returns series of the Taiwan stock index and stock index futures. Meanwhile, the non-linear intertemporal dependence in the squared returns series may come from the conditional heterogeneity in variance larger price changes that follow larger price changes. Additionally, based on the Lagrange multiplier test proposed by Engle (1982), the test statistics are all significantly larger than the critical value of chi-square distribution at 5% significant level for the whole sample period, estimation period, and test period. This observation leads to the rejection of the null hypothesis in which no ARCH effects occur. In short, the Taiwan stock index and stock index futures returns series have time-variant variances.

Based on the Engle and Ng's (1993) sign bias test (SBT), negative sign bias test (NSBT), positive sign bias test (PSBT), and joint test (JT), the volatility of Taiwan stock index returns and stock index futures returns exhibits a conditional heteroskedasticity and asymmetry.

Minimum variance portfolio and hedging effectiveness

A naive hedging effectiveness closer to 1 implies a hedging model with more effective hedging. Table 2 summarizes the hedging effectiveness of the various hedging models. The hedging effectiveness of the naive hedging model, 0.80404, is the lowest in static hedging models, suggesting that the hedging effectiveness of the naive hedging model is at least 0.80404 in static hedging models. Moreover, comparing the static hedging models with the dynamic hedging models in terms of hedging effectiveness reveals that the hedging effectiveness of the naive hedging model in the static hedging models, 0.80404, is the lowest. Meanwhile, the hedging effectiveness of VEC-GJR-MGARCH-t with a dynamic conditional correlation in the dynamic hedging models, 0.92787, is the highest.

This finding suggests that the dynamic hedging models has a higher hedging effectiveness than the static hedging models does, which is consistent with the conclusions of Kroner and Sultan (1993), Park and Switzer (1995), Tong (1996), Choudhry (2004), Lee and Yoder (2007a and 2007b), Switzer and El-Khoury (2007), and Kavussanos and Visvikis (2008). However, this finding differs from the conclusions of Holmes (1996), Yang and Lai (2009), and Park and Jei (2010). Table 2 also reveals that the hedging effectiveness of dynamic conditional correlation hedging models is better than that of constant conditional correlation hedging models. For instance, in the symmetric t distribution, the hedging effectiveness of the dynamic conditional correlation model (VEC-MGARCH-t), 0.90779, is higher than that of the constant conditional correlation model (VEC-MGARCH-t), 0.85685. In an asymmetric normal distribution, the hedging effectiveness of the dynamic conditional correlation model (VEC-GJR-MGARCH-n), 0.94744, is

Table 1. Summary statistics and ARCH analysis.

Variable	Taiwan stock index return			Taiwan stock index futures return		
	Whole sample period (1998/7/21 to 2010/10/29)	Estimation period (1998/8/14 to 2009/10/30	Test period (2009/11/1 to 2010/10/29)	Whole sample period (1998/7/21 to 2010/10/29)	Estimation period (1998/8/14 to 2009/10/30	Test period (2009/11/1 to 2010/10/29)
Number of samples	3101	2832	250	3101	2832	250
Mean	0.00134	-0.00010	0.04900	0.00101	-0.00003	0.05287
Standard deviation	1.58810	1.62923	1.08179	1.89434	1.94697	1.229641
Skewness	-0.11631**	-0.09631*	-0.83340	-0.16735**	-0.15638**	-0.57151
Excess kurtosis	3.84290**	4.70672**	4.79979**	11.03107**	10.76739**	4.05905**
Jarque-Bera	445.67597**	348.10118**	62.43111**	8345.47416**	7130.75405**	25.19146**
LB *Q* (6)	21.90030**	21.12110**	7.84260	18.45060**	18.54220**	9.92470
LB *Q*2(6)	443.3848**	381.36440**	8.99350	469.35820**	421.9093**	12.27570
ARCH	198.67620* (0.02181)	182.77070* (0.02236)	106.57870* (0.01461)	3503.98800* (0.02760)	3216.21900* (0.02842)	125.74950* (0.01730)
SBT	5.39690* (1.95738)	3.83130 (1.92265)	12.67570** (1.89060)	4.96400* (3.16230)	5.14600* (3.11991)	3.89380* (1.72675)
NSBT	39.17560** (1.94708)	34.52230** (1.91257)	0.48940 (1.93931)	177.59860** (3.0783)	165.1303** (3.03590)	0.73590 (1.74006)
PSBT	4.90410* (1.95781)	3.66060 (1.92296)	3.79190 (1.92649)	1.16040 (3.16475)	0.86000 (3.12277)	4.12040* (1.72830)
JT	681.62598*	637.96963*	63.94414*	468.68541*	437.22919*	66.20721*

1. ** (*) denotes statistical significance at 1% (5%) significant level.
2. LB Q (6) represents Ljung-Box Q test statistics of lag 6; the critical value is 16.81 (12.59) at 1% (5%) significant level.
3. LB Q2 (6) refers to Ljung-Box Q test statistics of lag 6 for squared series; the critical value is 16.81 (12.59) at 1% (5%) significant level.
4. The ARCH test statistics proposed by Engle (1982) are based on the minimum of AIC as the time lags of the Taiwan stock index and futures returns are determined under the null hypothesis; no ARCH effects.
5. SBT, NSBT, and PSBT denote a sign bias test, negative sign bias test, and positive sign bias test, respectively.
6. JT refers to a joint test, and it is a chi-square distribution with 3 degrees of freedom. The critical value at 5% significant level is 7.82.
7. The figures in brackets denote standard errors.

larger than that of the constant conditional correlation model (VEC-GJR-MGARCH-n), 0.90772. Moreover, the symmetric model has a higher hedging effectiveness than that of asymmetric models. For instance, the constant conditional correlation model (VEC-GJR-MGARCH-t) has a higher hedging effectiveness (0.88427) than that of the constant conditional correlation model (VEC-MGARCH-t) (0.85685). This difference can be attributed to the asymmetric volatility. Additionally, F test suggests that the hedging effectiveness of a hedging model is significantly

Table 2. Hedging effectiveness of the various hedging models.

Hedging model				Hedging effectiveness
Static hedging model			Naive hedging model	0.80404**(5.10317)
			Naive OLS model	0.82339**(5.66212)
Dynamic hedging model	Constant conditional correlation	Symmetric	VEC-MGARCH-t	0.85685**(8.64069)
			VEC-MGARCH-n	0.89153**(6.98587)
		Asymmetric	VEC-GJR-MGARCH-t	0.88427**(13.86380)
			VEC-GJR-MGARCH-n	0.90772**(10.84469)
	Dynamic conditional correlation	Symmetric	VEC-MGARCH-t	0.90779**(10.83632)
			VEC-MGARCH-n	0.93117**(9.21934)
		Asymmetric	VEC-GJR-MGARCH-t	0.92787**(19.02621)
			VEC-GJR-MGARCH-n	0.94744**(14.52911)

1. VEC-MGARCH-t refers to a situation in which a multivariate GARCH model with a vector error correction term follows t distribution. VEC-MGARCH-n refers to a situation in which a multivariate GARCH model with a vector error correction term follows normal distribution. VEC-GJR-MGARCH-t refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows t distribution. VEC-GJR-MGARCH-n refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows normal distribution.
2. Test period is one year. Hedging effectiveness is calculated from equation 17.
3. F statistic is used to test hedging effectiveness. **(*) denotes statistical significance at 1% (5%) significant level which the critical value is 1.34405(1.23229).

Table 3. Dynamic hedging effectiveness of the dynamic hedging models.

Dynamic hedging model			Dynamic hedging effectiveness	
			Naive hedging model	Naive OLS model
Constant conditional correlation	Symmetric	VEC-MGARCH-t	0.26950**(1.69320)	0.18949**(1.52606)
		VEC-MGARCH-n	0.44647**(1.36893)	0.38584*(1.23379)
	Asymmetric	VEC-GJR-MGARCH-t	0.40940**(2.71670)	0.34471**(2.44852)
		VEC-GJR-MGARCH-n	0.52907**(2.12509)	0.47749**(1.91531)
Dynamic conditional correlation	Symmetric	VEC-MGARCH-t	0.52943**(2.12345)	0.47789**(1.91383)
		VEC-MGARCH-n	0.64876**(1.80659)	0.61029**(1.62825)
	Asymmetric	VEC-GJR-MGARCH-t	0.63191**(3.72831)	0.59159**(3.36027)
		VEC-GJR-MGARCH-n	0.73178**(2.84707)	0.70241**(2.56603)

1. VEC-MGARCH-t refers to a situation in which a multivariate GARCH model with a vector error correction term follows distribution. VEC-MGARCH-n refers to a situation in which a multivariate GARCH model with a vector error correction term follows normal distribution. VEC-GJR-MGARCH-t refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows t distribution. VEC-GJR-MGARCH-n refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows normal distribution.
2. Test period is one year. Dynamic hedging effectiveness is calculated from equation 18.
3. F statistic is used to test hedging effectiveness. **(*) denotes statistical significance at 1% (5%) significant level which the critical value is 1.34405(1.23229).

higher than that of an unhedging model at 5% significant level.

Table 3 shows the dynamic hedging effectiveness of the dynamic hedging models, in comparison with static hedging models. All dynamic hedging effectiveness values are positive, suggesting that dynamic hedging models are better than the static hedging model in terms of dynamic hedging effectiveness, possibly owing to that

Table 4. Hedging effectiveness of the dynamic conditional correlation hedging models.

Dynamic conditional correlation hedging model		Hedging effectiveness of dynamic conditional correlation
Symmetric	VEC-MGARCH-t	0.24226*(1.25410)
	VEC-MGARCH-n	0.20262*(1.31971)
Asymmetric	VEC-GJR-MGARCH-t	0.25359**(1.37237)
	VEC-GJR-MGARCH-n	0.27133*(1.33974)

1. VEC-MGARCH-t refers to a situation in which a multivariate GARCH model with a vector error correction term follows t distribution. VEC-MGARCH-n refers to a situation in which a multivariate GARCH model with a vector error correction term follows normal distribution. VEC-GJR-MGARCH-t refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows t distribution. VEC-GJR-MGARCH-n refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows normal distribution.
2. Test period is one year. Hedging effectiveness is calculated from equation 19.
3. F statistic is used to test hedging effectiveness. ** (*) denotes statistical significance at 1% (5%) significant level which the critical value is 1.34405(1.23229).

Table 5. Asymmetric dynamic hedging effectiveness of the asymmetric dynamic hedging models.

Asymmetric dynamic hedging model		Asymmetric dynamic hedging effectiveness
Constant conditional correlation	VEC-GJR-MGARCH-t	0.35583**(1.60448)
	VEC-GJR-MGARCH-n	0.40776**(1.55238)
Dynamic conditional correlation	VEC-GJR-MGARCH-t	0.37675**(1.75578)
	VEC-GJR-MGARCH-n	0.39916**(1.57594)

1. VEC-MGARCH-t refers to a situation in which a multivariate GARCH model with a vector error correction term follows t distribution. VEC-MGARCH-n refers to a situation in which a multivariate GARCH model with a vector error correction term follows normal distribution. VEC-GJR-MGARCH-t refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows t distribution. VEC-GJR-MGARCH-n refers to a situation in which a multivariate GJR-GARCH model with a vector error correction term follows normal distribution.
2. Test period is one year. Asymmetric dynamic hedging effectiveness is calculated from equation 20.
3. F statistic is used to test hedging effectiveness. **(*) denotes statistical significance at 1% (5%) significant level which the critical value is 1.34405(1.23229).

the hedge ratio of the dynamic hedging models takes dynamics into account. Additionally, F test suggests that the hedging effectiveness of the dynamic hedging models is significantly better than that of the static hedging models at 5% significant level.

Table 4 shows the Hedging effectiveness of the dynamic conditional correlation hedging models. All hedging effectiveness values of the dynamic conditional correlation models are positive, suggesting that the dynamic conditional correlation hedging models are better than constant conditional correlation hedging models. This is possibly owing to that the hedging effectiveness of dynamic conditional correlation hedging models takes dynamics into account. In particular, the asymmetric VEC-GJR-MGARCH-n model has a hedging effectiveness of up to 27.133%. Additionally, F test suggests that the hedging effectiveness of dynamic conditional correlation hedging model is significantly better than that of constant conditional correlation hedging models at 5% significant level.

Table 5 shows the asymmetric dynamic hedging effectiveness of the asymmetric dynamic hedging models in comparison with symmetric models under the same distribution. All of the asymmetric dynamic hedging effectiveness values are positive, suggesting that asymmetric dynamic hedging models are better than symmetric dynamic hedging models. In particular, effectiveness of asymmetric dynamic hedging for the VEC-GJR-MGARCH-n model with a constant conditional correlation was up to 40.776% better. Additionally, the F test suggests that the hedging effectiveness of the dynamic asymmetric hedging models is significantly better than that of the dynamic symmetric hedging models at 5% significant level.

Conclusions

This study examines the asymmetric dynamic hedging effectiveness the Taiwan stock index futures by using daily data the Taiwan stock exchange capitalization weighted stock index (TAIEX) and index futures (TAIFEX) from July 21, 1998 to October 29, 2010. Based on the minimum-variance hedging portfolio, the hedging effectiveness of various hedging models is also examined, including dynamic hedging effectiveness, hedging effectiveness of dynamic conditional correlation, and asymmetric dynamic hedging effectiveness. Based on those results, we conclude the following:

(1) Comparing various hedging models in terms of hedging effectiveness reveals that the hedging effectiveness of the naive hedging model in static hedging models, 0.80404, is the lowest among all of the models. This finding suggests that in static hedging models, the hedging effectiveness of the naive hedging model is at least 80.404%. Additionally, comparing the static hedging models with the dynamic hedging models reveals that the naive OLS model has the lowest hedging effectiveness, 0.80404, among the static hedging models. Meanwhile, the VEC-GJR-MGARCH-t model with the dynamic conditional correlation has the highest hedging effectiveness, 0.94744, among the dynamic hedging models. This finding suggests that the dynamic hedging model has a higher hedging effectiveness than that of static hedging models;
(2) Comparing the dynamic conditional correlation hedging models with the constant conditional correlation hedging models reveals that the former has a higher hedging effectiveness than that of the latter. In particular, the asymmetric VEC-GJR- MGARCH-n model has a hedging effectiveness that is up to 27.133% higher.
(3) All asymmetric hedging effectiveness values are positive, suggesting that the asymmetric dynamic hedging model has a higher hedging effectiveness than the symmetric dynamic hedging models. In particular, the VEC-GJR-MGARCH-n model with a constant conditional correlation has an asymmetric hedging effectiveness that is up to 40.776% higher.

RECOMMENDATIONS

Although capable of reducing certain spot risks, futures contracts cannot eliminate entirely such risks. Therefore, investors highly prioritize risk management and should have a keen insight into investments to reduce risks.

As this study focused on the minimum-variance portfolio, we recommend that future studies adopt the utility function of risk and returns to measure. Additionally, the market sector is vulnerable to both daily news events and events that are unusual; these are also known as normal innovations and unusual or jump innovations, respectively. The conditional variance of jump innovations determines unusual and extreme price changes from significant news. We thus recommend that future studies adopt an autoregressive conditional jump intensity (ARJI) model to determine the continuous, discontinuous, and asymmetric jumps of volatility in the market. For other index targets and their derivatives products, we also recommend that future studies investigate asymmetric hedging effectiveness of the derivatives to construct the minimum-variance portfolio with those derivatives.

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