Hedging Effectiveness Comparison between Emerging and Developed Futures Exchanges

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ABSTRACT

This research estimated hedge ratios by using two econometric models: constant hedge ratios (ordinary least square technique, OLS; vector autoregressive model, VAR; and vector error correction model, VECM) and dynamic hedge ratios (DVEC-GARCH). These hedge ratios developed using these models were tested for hedging effectiveness by the amount of average variance reduction between the hedged and unhedged positions for indices, gold, and single stock futures contracts in three futures exchanges: the US exchange (CME) as a well-developed exchange, the Taiwan Futures Exchange (TFX) and the Thailand Futures Exchange (TFEX) as two emerging exchanges. The constant hedge ratio models were superior to the dynamic hedge ratios and the VECM model performed better than the VAR or OLS models, while, the DVEC-GARCH model could reduce the portfolio variance the least. Nevertheless, variance reduction of the portfolio can be efficiently done about 80 percent for every exchange.

Keywords: hedge ratio, hedging effectiveness, futures contracts, emerging exchange, developed exchange

บทคัดย่อ

งานวิจัยนี้มีจุดประสงค์เพื่อประมาณค่าอัตราถัวความเสี่ยง (hedge ratio) ผ่านแบบจำลองเศรษฐมิติ ซึ่งสามารถแบ่งได้ 2 กลุ่ม คือ แบบจำลองที่ให้อัตราถัวความเสี่ยงแบบคงที่ (constant hedge ratio) ได้แก่ แบบจำลอง OLS, VAR, VECM และ แบบจำลองที่ให้อัตราถัวความเสี่ยงที่เปลี่ยนแปลงแบบพลวัต (dynamic hedge ratio) คือ แบบจำลอง DVEC-GARCH และทดสอบประสิทธิภาพในการป้องกันความเสี่ยง (hedging effectiveness) สำหรับช่วง in-sample และ out-of-sample ด้วยการพิจารณาการลดลงของความผันผวนของกลุ่มการลงทุนที่มีการป้องกันความเสี่ยงเทียบกับกรณีกลุ่มการลงทุนที่ไม่มีการป้องกันความเสี่ยง โดยศึกษาในสัญญาซื้อขายล่วงหน้าของสินทรัพย์ทางการเงินที่สำคัญ ได้แก่ ดัชนีราคาหลักทรัพย์ ทองคำ และหุ้นสามัญ เปรียบเทียบระหว่าง ตลาดอนุพันธ์พัฒนาแล้ว คือ สหรัฐอเมริกากับตลาดอนุพันธ์เกิดใหม่ คือ ไต้หวัน และไทย ทั้งนี้ กลุ่มการลงทุนที่ใช้แบบจำลองในกลุ่มอัตราถัวความเสี่ยงแบบคงที่ สามารถลดความผันผวนของกลุ่มการลงทุนได้ดีกว่าแบบจำลองในกลุ่มอัตราถัวความเสี่ยงแบบพลวัต โดยแบบจำลอง VECM จะมีประสิทธิภาพดีที่สุด รองลงมาคือ แบบจำลอง VAR และ OLS ในขณะที่แบบจำลอง DVEC-GARCH มีประสิทธิภาพต่ำที่สุด เป็นที่

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น่าสังเกตว่าประสิทธิภาพในการลดความผันผวนของกลุ่มการลงทุนสามารถทำได้เกินร้อยละ 80 ในทุกตลาด
คำสำคัญ: อัตราถัวความเสี่ยง ประสิทธิภาพการป้องกันความเสี่ยง สัญญาซื้อขายล่วงหน้า ตลาดอนุพันธ์เกิดใหม่ ตลาดอนุพันธ์พัฒนาแล้ว

INTRODUCTION

Using a futures contract to protect price risks of the same amount of underlying assets cannot hedge all price risks because futures and spot prices do not move together perfectly or these two prices are always different due to basis risks. Such basis risks can cause inefficiencies in the usage of futures contracts to manage price risks. Traditional hedging strategies involve taking a hedging position in futures exchanges with a one-to-one position by selling or buying one future contract covering the same amount of underlying assets for both the spot and futures markets. This one-to-one strategy will cover all price risks if both the spot and futures prices move together or in same directions.

Our research investigated four econometric models for estimating the optimal hedge ratios between future contracts and underlying assets with the purpose of using futures contracts effectively for price risk management. These hedge ratio numbers are important for both hedgers and speculators because they can suggest the optimal number of futures contracts against the price risks covering the underlying assets. For many years, many economists have tried to find the optimal hedge ratio by using various econometric tools. Past literature suggests that those econometric tools could be used efficiently in well-developed futures exchanges. However, studies in the literature on using futures contracts to protect price risks in developing futures exchanges are rare. Therefore, in order to extend the study of usages of futures contracts to hedge price risks in emerging exchanges, this research compared the hedging effectiveness among various econometric tools to find an appropriate model for price risk protection in emerging futures exchanges (Taiwan and Thailand) compared to a well developed futures exchange (USA).

LITERATURE REVIEW

Past studies have determined hedge ratios by using different econometric tools to find the best model to estimate the optimal hedge ratio. The results of those studies demonstrate that either the same or different optimal hedge ratios resulting from those studies are due to differences in data sources, the study period, and econometric methodologies.

Ederington (1979) tested the hedging effectiveness of futures contracts using the ordinary least square technique (OLS) to estimate hedge ratios. The results showed that hedging for price risk management will be more effective when the OLS model explanation power or R^2 is higher. Herbst, Kare and Marshall (1993) considered that using the OLS model to estimate the hedge ratio was not effective because estimating the optimal hedge ratio faces serial correlation regression problems in the OLS residuals. Thus, an expectation of futures prices depending on information using the OLS model to estimate the optimal hedge ratio could include estimation mistakes.

Ghosh (1995) developed a new model, the vector error correction model (VECM), for studying hedging effectiveness in order to solve the OLS weakness of autocorrelation problems of the error terms during the estimation procedure. The information of international daily exchange rates in Ghosh's study showed that the variables used in the analysis were non-stationary and had a long term relationship. His results revealed that the VECM model outperformed the OLS model in estimating the hedge ratio..

However, both of these original econometric tools (OLS and VECM) involve analysis with the assumption that the variance of the disturbance terms is always constant. In reality, information in financial markets is always volatile. Thus the original models might not be suitable for estimating the hedge ratio in such a volatile financial environment. Researchers have tried to develop a new model for hedging objectives, resulting in the generalized autoregressive conditional heteroskedasticity (GARCH) model.

Casillo (2004) studied hedge ratios using the vector autoregressive (VAR), VECM, and GARCH models with daily information from the Milan Stock Index (MIB30) and the Milan Futures Index Price (FIB30) from 28 November, 1994 until 10 June, 2004. Because data used for analysis in that study were non-stationary and had a long term relationship, the results of the hedging effectiveness comparison among all the models in order to estimate the hedge ratio showed that the GARCH model performed best in reducing price risks and provided good compensation when compared to the other models.

Bhaduri and Durai (2008) studied the futures exchange of India and found that the compensation of the GARCH model gave the best results while the OLS model could reduce price risks better than the other models for a short term hedge. In contrast, the GARCH model was better than other models for a long term hedge. Yang (2001) studied the Australian futures exchange and reported that the GARCH model was the most effective for a long term hedge. A few studies on hedging effectiveness in small emerging futures exchanges (e.g. the Thailand Futures Exchange), such as Wisoot (2008) and Tina (2008), reported on hedging effectiveness and a suitable model for estimating the optimal hedge ratio in Thai futures exchanges. They tested four econometric models in the Thailand Futures Exchange (TFEX) and the Agricultural Futures Exchange of Thailand (AFET), respectively. They found that the GARCH model was the most effective for in-sample periods, and while the results from out-of-sample periods were different from the in-sample periods, the static hedge strategy outperformed the GARCH model.

Therefore, hedgers or investors who intend to protect price risks for their underlying assets in emerging exchanges need to find an optimal number of futures contracts in order to cover hedging objectives effectively. In determining the optimal hedging ratio, investors will try not to accumulate too high a cost of hedging or buy too many futures contracts unnecessarily.

RESEARCH METHODOLOGY

Hedge ratio and hedging effectiveness

In this study, four econometric models were employed to estimate the optimal hedge ratio: the conventional ordinary least square (OLS) technique, the vector autoregressive model (VAR), the vector error correction model (VECM), and the bivariate generalized autoregressive conditional heteroskedasticity (VAR-GARCH) model. The OLS, VAR, and VECM models estimate constant hedge ratios whereas time-varying optimal hedge ratios are calculated using the bivariate GARCH model (developed by Bollerslev, Engle, & Wooldridge, 1988). In this section, we discuss hedge ratios and hedging effectiveness. Then, all four econometric models are presented.

The optimal hedge ratio is defined as the ratio between taken sizes of a position in futures exchange and sizes of a cash position which minimizes the total risk of that portfolio. Hence, in order to know which model provides the best fit for obtaining the optimal hedge ratio, we compare the hedging effectiveness of each hedge ratio obtained using the four econometric tools. The returns and variances of unhedged and hedged portfolios can be calculated for comparing hedging effectiveness.

Returns of unhedged and hedged portfolios are calculated using Equation 1:

$$R_{unhedged} = S_{t+1} - S_t \quad (1)$$

$$R_{hedged} = (S_{t+1} - S_t) - h^*(F_{t+1} - F_t) \quad (2)$$

where S_t and F_t are the logarithm at time t of the spot and futures prices, respectively, S_{t+1} and F_{t+1} are the logarithm at time t_{+1} of the spot and futures prices, respectively, $R_{unhedged}$ and R_{hedged} are the unhedged and hedged returns, and h^* is the hedge ratio of each model.

Variances of unhedged (U) and hedged portfolios (H) are calculated using Equations 3 and 4, respectively:

$$Var(U) = \sigma_S^2 \quad (3)$$

$$Var(H) = \sigma_S^2 + H^2\sigma_F^2 - 2H\sigma_{S,F} \quad (4)$$

where H is the optimal hedge ratio, σ_S^2 and σ_F^2 are variances of returns of the spot and futures prices, and σ_{S+F} is the covariance between the returns of the spot and futures prices. Therefore, the effectiveness of hedging is estimated as the percentage decrease in the variance of a hedged portfolio compared to an unhedged portfolio, as shown in Equation 5:

$$\text{Hedging Effectiveness (E)} = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \quad (5)$$

Models for calculating hedge ratios

The econometric models used to estimate the hedge ratios are classified into two groups: (1) models of constant hedge ratios, such as the OLS, VAR and VECM models, and (2) models of dynamic hedge ratio, such as the DVEC-GARCH model

Ordinary least square (OLS) model: The OLS model is a simple linear regression between the returns on the spot prices and the returns on the futures prices as shown in Equation 6:

$$\Delta S_t = \alpha + \beta\Delta F_t + \varepsilon_t, \quad (6)$$

where ΔS_t and ΔF_t are the returns of the spot and futures at time t, respectively, β is the slope of the regression formula representing the hedge ratio (h*), α is the intercept term, and ε_t is the error term.

Bivariate vector autoregressive (Bi-VAR or VAR) model: The VAR model was developed to solve the drawbacks of the OLS model. We can consider how independent variables influence other dependent variables using Equations 7 and 8:

$$\Delta S_t = c_s + \sum_{i=1}^{k}\beta_{si}\Delta S_{t-i} + \sum_{j=1}^{l}\lambda_{sj}\Delta F_{t-j} + \varepsilon_{st} \quad (7)$$

$$\Delta F_t = c_f + \sum_{i=1}^{k}\beta_{fi}\Delta S_{t-i} + \sum_{j=1}^{l}\lambda_{ji}\Delta F_{t-j} + \varepsilon_{ft} \quad (8)$$

where ΔS_t and ΔF_t are returns of the spot and futures at time t, the lagged returns of the spot and futures prices are presented at time $t-i$ and $t-j$, c_s and c_f are the intercepts and their coefficients are in front of the lagged returns, and ε_{st} and ε_{ft} are randomly and independently distributed error terms. Residual series are used to estimate the hedge ratios. If σ_{ss} and σ_{ff} are the variances of the returns of the spot and futures prices and σ_{sf} is the covariance between the returns of the spot and futures prices, then

$$Var(\varepsilon_{st}) = \sigma_{ss},\ Var(\varepsilon_{ft}) = \sigma_{ff},\ Cov(\varepsilon_{st}, \varepsilon_{st}) = \sigma_{sf}$$

Thus, the hedge ratio with the lowest portfolio volatility is determined by Equation 9:

$$h^* = \frac{\sigma_{sf}}{\sigma_{ff}} \quad (9)$$

Vector eerror ccorrection (VECM) model: The VAR model does not include results where the two series might co-integrate. Hence, if the VAR model has no error-correction terms representing movements of the long term balances between the spot and future prices, the hedge ratio obtained by the VAR model will be biased. Therefore, the VECM model was developed to replace the VAR model to solve this drawback as shown in Equations 10 and 11:

$$\Delta S_t = c_s + \sum_{i=2}^{k}\beta_{si}\Delta S_{t-i} + \sum_{j=2}^{l}\lambda_{si}\Delta F_{t-j} - \gamma_s Z_{t-1} + \varepsilon_{st} \quad (10)$$

$$\Delta F_t = c_f + \sum_{i=2}^{k} \beta_{fi} \Delta S_{t-i} + \sum_{j=2}^{l} \lambda_{fi} \Delta F_{t-j} - \gamma_f Z_{t-1} + \varepsilon_{ft} \quad (11)$$

where $Z_{t-1} = S_{t-1} - \alpha F_{t-1}$ is the error-correction term to measure how dependent variables deviate from the previous long term balances. All other variables are the same as represented in the VAR model. The hedge ratio of the VECM model is calculated in the same way for the VAR model according to Equation 9.

DVEC-GARCH model: The GARCH model was first mentioned by Bollerslev (1986). The model was developed from the autoregressive conditional heteroskedasticity or ARCH (q) model. The model was continuously developed until Bollerslev *et al.* (1988) modified the GARCH model from the univariate GARCH model to the multivariate GARCH (DVEC-GARCH) model. The last model is applied to estimate dynamice hedge ratios based on the conditional variance and covariance of the spot and future prices. All parameters are calculated from the returns of the spot and future prices. The DVEC-GARCH model is shown by the set in Equation 12 :

$$h_{ss,t} = c_{ss} + a_{ss}\varepsilon^2_{s,t-1} + b_{ss,t-1}h_{ss,t-1}$$

$$h_{sf,t} = c_{sf} + a_{sf}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + b_{sf,t-1}h_{sf,t-1}$$

$$h_{ff,t} = c_{ff} + a_{ff}\varepsilon^2_{f,t-1} + b_{ff,t-1}h_{ff,t-1} \quad (12)$$

where $h_{ss,\,t}$ and $h_{ff,\,t}$ are the conditional variances of the errors $\varepsilon_{s,t-1}$ and $\varepsilon_{f,t-1}$, respectively, and $h_{sf\,,t}$ is the conditional covariance. Hence, the set in Equation (12) represents a model of the dynamic hedge ratios which should provide a better estimate of the constant hedge ratio under volatile market conditions. The optimal hedge ratio, h*, of the DVEC-GRACH (1,1) model is calculated using Equation 13:

$$h^* = \frac{h_{sf,t}}{h_{ff,t}} \quad (13)$$

EMPIRICAL RESULTS

Characteristics of futures prices

This study used the daily closing price data of three financial asset classes (stock indices, gold, and single stock futures contracts). These futures contracts are traded on the US Futures Exchange (Chicago Mercantile Exchange: CME for S&P 500, NASDAQ 100 Indices and GC Gold contracts) as a well-developed exchange which was compared to two emerging futures exchanges (Taiwan Futures Exchange: TFX for the TAIEX Index and ASUS stock contracts, and the Thailand Futures Exchange: TFEX for the SET50 Index, gold futures (GF 10 baht and GF 50 baht) and PTT stock contracts).

The collected stock futures contracts in our study are highly liquid stock futures contracts in order to follow the efficient market hypothesis in the weak form suggested by the previous literature. The data range covered 4 January, 2010 to 20 June, 2012 for in-sample analysis except for the gold futures contracts that covered 4 January, 2011 to 20 June, 2012. For the out-of-sample analysis, all futures contract data covered 4 January 2012 to 20 June 2012.

Test of unit root and co-integration

The stationarity of returns is tested using the augmented Dickey-Fuller (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) statistics. The KPSS approach is often suggested as a confirmatory test of stationarity. The null hypothesis for the ADF test is that the series contains a unit root whereas the stationarity of a series is used as the null hypothesis for the KPSS test. The KPSS statistics involve a Lagrange multiplier (LM) test.

Both the ADF and KPSS test statistics confirm that the return series are stationary by rejecting the null hypothesis of the existence of a unit root from the ADF test and accepting stationarity from the KPSS test (The results are not shown in this article). Then, the co-integration between the spot and futures prices is tested by

Johansen's (1991) maximum likelihood method. The null hypothesis is tested on the hypothesized number (no.) of co-integrating equations (CE) that show co-integration between the spot and futures prices (The results are not shown.). We observe that the spot and futures prices have one co-integrating vector and they are co-integrated in the long run because the null hypothesis of no CE is rejected.

Hedge ratio and hedging effectiveness: Empirical performance of models

Hedge ratios and the hedging effectiveness of the indices futures, gold futures, and single stock futures contracts were estimated using the four econometric models (OLS, VAR, VECM and DVEC-GARCH models) described earlier. The in-sample and out-of-sample estimates of the hedge ratios and hedging effectiveness were calculated from these models and compared.

In-sample results

OLS estimates: For all futures contracts, Table 1 shows that hedge ratios (β) are higher than 0.80 except for the ASUS single stock futures contracts of the TFX. The hedge ratios estimated by the OLS method provide approximately 80 percent variance reduction (hedging effectiveness seen by R^2) except for the ASUS contract at only 43.19 percent . In the case of the indices futures contracts, the hedging effectiveness is higher than 90 percent for the S&P 500 and TAIEX futures contracts, while the SET50 and NASDAQ 100 futures contracts could protect nearly 90 percent of the risk. For the gold futures contracts, hedging effectiveness is the highest for the GC Gold futures contracts (CME). The Gold 10 baht and Gold 50 baht futures contracts of the TFEX provide 83 percent and 85 percent hedging effectiveness, respectively. In the case of the single stocks futures, the PTT futures contracts provide 85 percent hedging effectiveness while the ASUS futures contracts could protect risk at a level of only 43 percent.

VAR estimates: Table 2 shows that the hedge ratios calculated from the VAR model are higher and perform better than the OLS estimates in reducing portfolio variance except for the ASUS contract, where the hedge ratio estimated through the VAR model reduced from 0.67 (OLS estimate) to 0.65, but the hedging effectiveness increased from 43 percent in the case of OLS to 73 percent from the VAR approach.

VECM estimates: Although the VECM model does not consider the conditional covariance structure of the spot and futures price that changes

Table 1 OLS regression model estimates

Asset	α	β	R^2
Index			
NASDAQ 100	-0.000038	0.936547	0.896827
S&P 500	-0.000020	0.929475	0.935542
SET50	-0.000134	0.847680	0.871140
TAIEX	0.000021	0.899586	0.921166
Gold			
GF 10 baht	-0.000128	0.875014	0.837641
GF 50 baht	-0.000117	0.889234	0.853092
GC Gold	0.000000	0.997442	0.994639
Stock			
ASUS	-0.000340	0.670602	0.431872
PTT	-0.000061	0.903530	0.847074

over time, it is supposed to be the best specified model for estimations of constant hedge ratios and hedging effectiveness because it captures any long term co-integration between the spot and futures prices. Table 3 shows that the in-sample performance of the VECM model provides better variance reduction than the VAR and OLS models. Moreover, the OLS estimate seems to be the least efficient in variance reduction.

Table 2 Estimation of hedge ratio and hedging effectiveness

Asset	Covariance (ε_F,ε_S)	Variance (ε_F)	Hedge Ratio (h*)	Variance (ε_S)	Variance (H)	Variance (U)	Hedging effectiveness (E)
Index							
NASDAQ 100	0.000162	0.000165	0.981818	0.000169	0.000009	0.000170	0.941544
S&P 500	0.000144	0.000150	0.960000	0.960000	0.000008	0.000152	0.949022
SET50	0.000198	0.000225	0.878530	0.000192	0.000019	0.000193	0.868181
TAIEX	0.000143	0.000155	0.922581	0.000143	0.000011	0.000146	0.924029
Gold							
GF 10 baht	0.000103	0.000118	0.872881	0.000103	0.000013	0.000106	0.876512
GF 50 baht	0.000102	0.000116	0.879310	0.000102	0.000012	0.000106	0.883896
GC Gold	0.000134	0.000134	1.000000	0.000134	0.000000	0.000133	1.000000
Stock							
ASUS	0.000448	0.000686	0.653061	0.000492	0.000199	0.000729	0.726235
PTT	0.000317	0.000347	0.913545	0.000326	0.000036	0.000333	0.890556

Table 3 Estimation of hedge ratio and hedging effectiveness

Asset	Covariance (ε_F,ε_S)	Variance (ε_F)	Hedge Ratio (h*)	Variance (ε_S)	Variance (H)	Variance (U)	Hedging effectiveness (E)
Index							
NASDAQ 100	0.000190	0.000192	0.989583	0.000197	0.000009	0.000170	0.947224
S&P 500	0.000174	0.000179	0.972067	0.000176	0.000007	0.000152	0.954932
SET50	0.000245	0.000277	0.884477	0.000235	0.000018	0.000192	0.904918
TAIEX	0.000193	0.000206	0.936893	0.000191	0.000010	0.000146	0.930146
Gold							
GF 10 baht	0.000142	0.000166	0.855422	0.000135	0.000014	0.000106	0.872362
GF50 baht	0.000138	0.000161	0.857143	0.000132	0.000014	0.000106	0.870655
GC Gold	0.000163	0.000163	1.000000	0.000163	0.000000	0.000133	1.000000
Stock							
ASUS	0.000557	0.000823	0.676792	0.000578	0.000201	0.000729	0.724042
PTT	0.000361	0.000401	0.900249	0.000363	0.000038	0.000333	0.885739

Bivariate GARCH estimates (DVEC-GARCH model): The bivariate GARCH model is used to modify the estimation of the hedge ratio for time-varying volatility and to incorporate non-linearity in the mean equation. Although errors of the VAR and VECM models are analyzed for the presence of the 'ARCH effect', there were still errors of time-varying volatility. Hence, the time-varying hedge ratios were estimated using the constant conditional correlation assumption and time-varying covariance structure of the spot and futures prices. Because time-varying hedge ratios vary across time, we have shown the descriptive statistics of these time-varying hedge ratios, with the statistical parameters of time-varying hedge ratios obtained from the DVEC-GARCH model for indices, gold, and single stock futures contracts presented in Table 4.

The average (mean) hedge ratios estimated from the time-varying conditional variances and covariance between the spot and futures returns were lower than in other methods (except the GF 50 baht contracts). The average optimal hedge ratios for the SET50, S&P 500, NASDAQ 100 and TAIEX were 0.835843, 0.949008, 0.975420 and 0.903565, respectively. For the GC Gold futures, Gold 10 baht and Gold 50 baht futures contracts, the hedge ratios were 0.988480, 0.932560 and 0.988480, respectively. For the PTT and ASUS single stock futures contracts, the hedge ratios were 0.890062 and 0.569731, respectively.

The constant hedge ratios obtained from the OLS, VAR, and VECM models and the average time-varying hedge ratios obtained from the DVEC-GARCH model are compared in Tables 5 and 6.The results show that the hedge ratios calculated from the DVEC-GARCH model are slightly lower and provide a slightly lower variance reduction than the other models.

Out-of- sample results

The out-of-sample evaluation of the models is more appropriate because traders are concerned more with future performance. Thus, a model giving dynamic optimal hedge ratios might be more powerful when comparing performance with a model giving a constant hedge ratio. Data for period between 4 January 2012 and 20 June 2012 were used for the out-of-sample analysis for the indices, gold, and single stock futures contracts. For the OLS, VAR, and VECM models, the estimated hedge ratios from the previous estimation period were used

Table 4 GARCH estimates of hedge ratios form the bivariate diagonal GARCH (1,1) or the DVEC-GARCH model

Asset	Min	Max	Mean	SD
Index				
NASDAQ 100	0.670886	1.289641	0.975420	0.074615
S&P 500	0.756757	1.064655	0.949008	0.061486
SET50	0.292674	1.037037	0.835843	0.060670
TAIEX	0.735632	1.074866	0.903565	0.057979
Gold				
GF 10 baht	0.808219	2.78626	0.842628	0.141188
GF 50 baht	0.423664	1.187377	0.932560	0.109646
GC Gold	0.582222	1.054795	0.988480	0.039716
Stock				
ASUS	-0.200096	1.586279	0.569731	0.287810
PTT	0.414573	1.223404	0.890062	0.115508

Table 5 In-sample comparison of optimal hedge ratio estimates by different models

Asset	Hedge ratio			
	OLS	VAR	VECM	GARCH
Index				
NASDAQ 100	0.936547	0.981818	0.989583	0.975420
S&P 500	0.929475	0.960000	0.972067	0.949008
SET50	0.847680	0.878530	0.884477	0.835843
TAIEX	0.899586	0.922581	0.936893	0.903565
Gold				
GF 10 baht	0.875014	0.872881	0.855422	0.842628
GF50 baht	0.889234	0.879310	0.857143	0.932560
GC Gold	0.997442	1.000000	1.000000	0.988480
Stock				
ASUS	0.670602	0.653061	0.676792	0.569731
PTT	0.903530	0.913545	0.900249	0.890062

Table 6 In-sample comparison of optimal hedging effectiveness estimates by different models

Asset	Hedging effectiveness			
	OLS	VAR	VECM	GARCH
Index				
NASDAQ 100	0.896827	0.941544	0.947224	0.881397
S&P 500	0.935542	0.949022	0.954932	0.922023
SET50	0.871140	0.868181	0.904918	0.872027
TAIEX	0.921166	0.924029	0.930146	0.913909
Gold				
GF 10 baht	0.837641	0.876512	0.872362	0.828789
GF50 baht	0.853092	0.883896	0.870655	0.855027
GC Gold	0.994639	1.000000	1.000000	0.993387
Stock				
ASUS	0.431872	0.726235	0.724042	0.472923
PTT	0.847074	0.890556	0.885739	0.825437

for testing their out-of-sample performance. For the bivariate GARCH or DVEC-GARCH model, calculations involved one-period-ahead conditional variances and the covariance of the spot and futures prices using estimated parameters from the previous estimation periods. By overall results, out-of-sample results are quite similar to in-sample results.

The performance of the hedging effectiveness by the out-of-the-sample data compared among the constant hedge ratio models showed that the VAR and VECM models perform well and provide better variance reduction than the OLS model. Comparing the out-of-sample hedging effectiveness between the constant hedge ratio models and the dynamic hedge ratio model, the DVEC-GARCH model gave comparable results as shown in Table 7.

Comparing across all the futures contracts, the constant hedge ratio models (VAR and VECM) performed better than the dynamic hedge ratio

Table 7 Out-of-sample comparison of optimal hedging effectiveness of different models

Asset	Hedging effectiveness			
	OLS	VAR	VECM	GARCH
Index				
SET50	0.567742	0.750133	0.763027	0.710327
S&P 500	0.893552	0.926185	0.911935	0.914374
NASDAQ 100	0.857538	0.901959	0.920009	0.836582
TAIEX	0.911858	0.943047	0.935746	0.924212
Gold				
GF 10 baht	0.859811	0.915663	0.894917	0.870037
GF 50 baht	0.873129	0.921919	0.919771	0.901334
GC Gold	0.981152	0.990894	1.000000	0.998369
Stock				
PTT	0.713807	0.751432	0.768811	0.740263
ASUS	0.720052	0.825872	0.818345	0.689738

model based on the variance reduction percentage. Our results are different from Baillie and Myers (1991), Myers (1991), Engle and Kroner (1995), Yang (2001), Tina (2008), and Wisoot (2008), who reported that the dynamic hedge ratio model performed better than the constant hedge ratio models. Their findings might be true for volatile futures exchanges. Although the findings by Tina (2008) and Wisoot (2008) show that the dynamic hedge ratio model performed better than the constant hedge ratio models in the emerging Thailand futures exchange, it was only for the in-sample period. Nevertheless, their results for the out-of-sample periods were different from the in-sample period, where the static hedge strategy outperformed the GARCH model.

CONCLUSIONS

This study found that investors can use futures contracts to protect price risks by observing a decrease in the portfolio variance when their portfolio is hedged by futures contracts in both well-developed and emerging exchanges. Comparing the hedging effectiveness of both in-sample and out-of-sample tests, the constant hedge ratios were superior to the dynamic hedge ratio and the VECM model performed better than the VAR and OLS models, while the DVEC-GARCH model could reduce the portfolio variance the least. Because the futures and spots prices were found to be co-integrated in long run, our findings report why the VECM model outperformed the other models in terms of reducing portfolio variance.

Comparing hedging effectiveness between well-developed and emerging futures exchanges, for the indices of futures contracts, investors in a well-developed exchange (CME) can reduce their portfolio variance by more than 90 percent, while investors in emerging exchanges (TFX and TFEX) can achieve about 80 percent. For gold futures contracts, investors in a well-developed exchange can reduce their portfolio variance by nearly 100 percent and by about 90 percent in emerging exchanges. For single stock futures contracts, the portfolio variance of PTT futures contracts on the TFEX can be reduced by nearly 80 percent and by more than 80 percent for ASUS futures contracts on the TFX. The results of this study revealed that hedging efficiency in emerging futures exchanges, such as the TFX and TFEX, gives satisfactory price risk protection results when compared to same price risk protection performance of the well-developed futures exchange. If investors observe that the futures and spots prices co-integrate in the long run, the VECM model might outperform other models in decreasing their portfolio variance. Nevertheless, in strongly volatile markets, a model using dynamic hedge ratios might give better hedging effectiveness performance. However, a limitation of this study is the nature of commodity futures prices that might vary due to some macro-economic or seasonal factors. Unfortunately, these external factors can break down the EMH proposition.

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