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CURRENCY HEDGING STRATEGIES USING MULTIVARIATE GARCH MODELS

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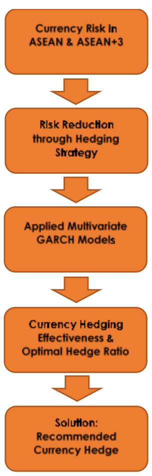
Graphical abstract



Abstract

Hedging on futures or forward markets is an important tool to reduce risk. Thus, in order to manage the currency risk, it is important to have a suitable hedging strategy. Hedging is a means to offset potential losses on investment by making the second investment, which is expected to move in the opposite way in the financial markets. Therefore, this study aims to identify the relationship between spot and futures contract exchange rates and spot and forwards contract exchange rates. Secondly, calculate the optimal hedge ratio in order for effective optimal portfolio design and hedging strategy using CCC, DCC and Diagonal-BEKK models. The data consist of daily closing prices of spot, futures and 3-month forwards contract for currencies within ASEAN and ASEAN+3 countries. The empirical results revealed that the best model for hedging effectiveness is found to be CCC and DCC. These two models are able to reduce the variance 59.64 percent for Japanese Yen, 97.42 percent for Malaysia Ringgit, 66.14 percent for Singapore Dollar and 93.42 for Philippine Peso. Hence, it can be suggested to investors to hedge Malaysia Ringgit since the currency has the highest reduction in risk.

Keywords: Exchange rates, Hedging effectiveness, ASEAN+3 countries, optimal hedge ratio, multivariate GARCH.

1.0 INTRODUCTION

The foreign exchange markets have become more competitive and volatile. The foreign exchange market is established as the most liquid and largest market in the financial institutions around the world [7]. The Multinational Companies (MNCs) and large international banks are the major participants in this market. The foreign exchange markets work through financial institutions, and operates on several levels. Dealers (most are banks) act as intermediary for foreign exchange trading involves hundreds of millions of dollars. Fluctuations in the exchange rate will give big impact to the foreign currency. The rise or fall of price in a day is affected by changes in exchange rates. This is especially true in the current economic situation in which the currency is constantly changing every day, this makes it more difficult to detect the rate of exchange applicable. Thus, in order to manage the currency risk, it is important to have the suitable hedging strategies.

Hedging is a tool to offset a potential loss on one investment by purchasing or shorting another investment which expected to perform in the contrary way. In our context, we used futures and forwards to hedge the spot exchange rates. In addition, hedging could help to reduce the volatility of an exchange rate portfolio by reducing the risk of loss. When hedgers have a position (long or buy) the base currency, usually they will sell (short) a futures contract or forward contracts as a tool for reciprocal investment. However, [10] debated on the number of contracts that need to be taken per unit of the base currency as well as the effectiveness measure to find that particular ratio. The optimal hedge ratio is very helpful in analyzing how much futures contracts that required to be held, while it effectiveness assesses the hedging performances and the usability of the strategies. Furthermore, these effectiveness ratio can be used by hedgers to compare the benefits of hedging a given position from alternative or a different contracts.

The objectives of this study are, first to investigate the relationship between spot, futures and forwards exchange rates market within ASEAN plus three countries (ASEAN+3). Second, to calculate the optimal hedge ratio (OHR) from the conditional covariance matrices using the multivariate conditional volatility GARCH models and compares the performance based on the hedging effectiveness.

2.0 LITERATURE REVIEW

[7] studied about the hedging effectiveness of the currency where they have applied the same model as the previous, [6]. They focused on investigating the optimal hedge ratios, optimal portfolio weights and the hedging effectiveness estimations. Their study indicates that USD/GBP can effectively reduce the portfolio risk. In addition, the use of USD/GBP and USD/ JPY currencies is highly effective in the near-month future contract. All four models do not give lots of information because it provides with similar results even though there is some differences seen in DCC and BEKK models, but the hedging strategies lead to reduce the volatility. A research conducted by [12] have used five world major international currencies and the result indicated that the conditional hedging model improved well in term of reducing the portfolio variance and transaction costs better than conventional models in currency markets.

Dynamic hedging approach also conducted by [5] based on Bivariate GARCH which also apply the jump model in currency spot and futures. The GARCH-jump model has been used due to the capability of its model in capturing the volatility and leptokurtosis of the joint distribution to the selected foreign currencies. They also noticed that the effectiveness of dynamic hedging with currency futures can reduce the transaction prices. [4] investigates the benefits of dynamic currency hedging during the financial crisis. By gathering daily data, the information before and during the Global Financial Crisis (GFC) and the Euro Sovereign Crisis (ESC) have been covered. From the result, the evidence has been found to assist European hedge fund managers in planning the development of their business in the future. During the financial crisis, currency hedging in foreign asset investment provides better performance compared to the simple European portfolio.

3.0 ECONOMETRICS MODEL

3.1 Constant Conditional Correlation

The Constant Conditional Correlation (CCC) GARCH has recently become popular among practitioners [2]. CCC has commonly been used where the model use time changing conditional variances and covariance but then assumed to be constant conditional correlation. Hence, the estimation is given by:

$$\begin{gathered} y_t = E(y_t|T_{t-1}) + \varepsilon_t \\ \varepsilon_t = D_t\eta_t \\ var(\varepsilon_t|T_{t-1}) = D_tRD_t \end{gathered} \tag{1}$$

where $y_t = E(y_{1t,\dots,}y_{mt})'$, $\eta_t = (\eta_{1t},\dots,\eta_{mt})'$ is a series of i.i.d. random vectors, T_t is considered as historical information at time t where $t = 1,\dots,n.$, $D_t = diag\sqrt{h_1,\dots,h_m}$. m is the number of assets. The conditional correlation matrix of CCC is $R = E(\eta_t\eta'_t|F_{t-1}) = E(\eta_t\eta')$, where $R = \{\rho_{ij}\}$ is positive definite with $\rho_{ii} = 1$; $i = 1,\dots,m$. The constant conditional correlation matrix of the unconditional shocks, η_t is equivalent to the constant conditional covariance matrix of the conditional shocks, ε_t from equation (1), $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta'_tD_t, D_t = \sqrt{diagQ_t}$, and $E(\varepsilon_t\varepsilon'_t|T_{t-1}) = Q_t = D_tRQ_t$, where $Q_t$is the conditional covariance matrix.The conditional covariance matrix, Q_t is positive definite if and only if all the conditional variances are positive and R is positive definite.Since all the diagonal elements are positive, so D_t will also be positive definite. To complete the specification, the dynamics of the conditional variances h_{it} ; $i = 1,\dots,m$ has to be defined. The constant conditional correlations (CCC) model relies on the following univariate GARCH (p,q) specifications:

$$H_{it} = \omega_i + \sum_{j=1}^{q}\alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{p}\beta_{ij}H_{i,t-j} \tag{2}$$

where α_{ij} is the ARCH effect or short-term retention of shocks to return i, β_{ij} is the GARCH effect and $\sum_{j=1}^{r}\alpha_{ij} + \sum_{j=1}^{s}\beta_{ij}$is long run persiatnce of the return shocks.

3.2 Dynamic Conditional Correlation

A dynamic conditional correlation (DCC) model that proposed by [8] is applied to allow the conditional correlation matrix time-dependent on the form:

$$y_t|T_{t-1} \sim N(0,Q_t) \tag{3}$$

$$Q_t = D_tR_tD_t \tag{4}$$

where $D_t = diag(H_1^{0.5},\dots,H_m^{0.5})$ is a diagonal matrix of conditional variances, T_t in time t is the information set available; $t = 1,2,\dots,n$. The conditional variance is estimated as univariate GARCH(p,q) model, allowing for different lag lengths for each series $i = 1,2,\dots,n$.

$$H_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{ik} \varepsilon_{i,t-k}^2 + \sum_{l=1}^{q} \beta_{ik} H_{i,t-k} \quad (5)$$

If η_t is a vector of i.i.d. random variables, with zero mean and unit variance, Q_t in Equation (6) is the conditional covariance matrix (after standardization), $\eta_{it} = y_{it}/\sqrt{H_{it}}$). The η_{it} will use to estimate the dynamic conditional correlations, as follows:

$$R_t = \{(diag(Q_t)^{-0.5})\}Q_t\{(diag(Q_t)^{-0.5}\} \quad (6)$$

where the $k \times k$ symmetric positive definite matrix Q_t is given by:

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 \eta_{t-1} \eta'_{t-1} + \theta_2 Q_{t-1}. \quad (7)$$

The effect of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation is captured by the scalar parameter, θ_1 and θ_2 respectively. θ_1 and θ_2 are nonnegative scalar parameters satisfying $\theta_1 + \theta_2 < 1$, which implies that $Q_t > 0$. $\bar{Q}$ in Equation (7) is equivalent to the CCC model when $\theta_1 = \theta_2 = 0$. Equation (7) is a conditional covariance matrix, and $\bar{Q}$ is the k x k unconditional variance matrix of η_t when Q_t is conditional on the vector of standardized residuals. A two-stage model established on the likelihood function can be estimated when DCC is not linear. Hence, in the first stage, the series must belong to univariate GARCH estimation and the second stage is used in ensuring correct correlation estimation to be applied.

3.3 Diagonal BEKK

[9] introduced another alternative dynamic conditional model that has positive definite on the conditional covariance matrices. The model named as Baba, Engle and Kroner (BEKK) and the multivariate GARCH(p,q) is given as:

$$H_t = C_0 C'_0 + \sum_{j=1}^{q} \left(A_j \varepsilon_{t-j} \varepsilon'_{t-j} A'_j\right) + \sum_{i=1}^{p} (B_i H_{t-i} B'_i) (8)$$

where A_0 is a lower triangular matrix $((N(N+1))/2)$ parameters, A_j and B_i are $(N \times N)$ diagonal matrices with typical elements α_{ij} and β_{ij} respectively and As long as $\mathrm{C}_0 \mathrm{C'}_0$ is a positive definite matrix, so the parameterization below will guarantee the H_t is also positive finite with $((N(N+1))/2) + N\text{^}2\,(q+p)$. [3] have proposed a simpler expression of H_t for BEKK, known as Diagonal-BEKK (p,q) model. The model is commonly applied as:

$$H_t = C_0 C'_0 + \sum_{j=1}^{q} \left(A_j \varepsilon_{t-j} \varepsilon'_{t-j} A'_j\right) + \sum_{i=1}^{p} (B_i H_{t-i} B'_i) (9)$$

where the matrices A_j and B_i are again restricted to being diagonal. The Diagonal-BEKK (p,q) model requires the estimation of $(N(N+1)/2) + N(q+p)$ parameters.

3.4 Optimal Hedge Ratio

Investor in futures market commonly use hedging approach which mirrors their outlooks towards risk and personal targets. This research has applied the hedging strategies by [7], considering the case of exchange rates. The returns on the portfolio for spot and futures position are represented as follows:

$$R_{H,t} = R_{s,t} - \gamma\, R_{f,t} \quad (10)$$

where $R_{H,t}$ is the returns on holding portfolio between t and $t-1$, $R_{s,t}$ and $R_{f,t}$ are the returns on holding spot and futures between time t and $t-1$ respectively. γ is the hedge ratio (the numbers of futures contract that the hedger should sell for each unit of spot). In other words, when there is a risk, investors are suggested to long (buy) one unit of spot position and hedged by short (sell) unit of futures. According to [11], the variance of the returns of a given hedged portfolio and restricted on the data set presented at time $t-1$ is denoted as follows:

$$var(R_{H,t}|\varphi_{t-1}) = var(R_{s,t}|\varphi_{t-1}) - 2\gamma cov(R_{s,t}, R_{f,t}|\varphi_{t-1}) + \gamma_t^2 var(R_{f,t}|\varphi_{t-1}) \quad (11)$$

where $var(R_{s,t}|\varphi_{t-1}), var(R_{f,t}|\varphi_{t-1})$ is the conditional variance of the spot and futures return and $cov(R_{s,t}, R_{f,t}|\varphi_{t-1})$ is the covariance of the spot and futures return. [1] setting the partial derivative in Equation (11) equal to zero with respect to $\gamma_t.\gamma_t$ yields the optimal hedge ratio (OHR) conditional on the information set available at $t-1$ as follows:

$$\gamma_t^*|\varphi_{t-1} = cov(R_{s,t}, R_{ft}|\varphi_{t-1}) \,/ var(R_{ft}|\varphi_{t-1}) \quad (12)$$

where $cov(R_{s,t}, R_{ft}|\varphi_{t-1})$ is the covariance of spot and futures/ forwards, and $var(R_{ft}|\varphi_{t-1})$ is the variance of futures/ forwards

3.5 Hedging Effectiveness

Three multivariate GARCH models are used to estimate the optimal hedge ratio. Then, the hedging performance of these three models are evaluated and compared. Following [13], he suggested a hedging effective index (HE) can be used in measuring the variation decrement for any hedged portfolio with the unhedged portfolio. The effective index available as:

$$HE = [\sigma^2{}_{unhedged} - \sigma^2{}_{hedged}]/\sigma^2{}_{hedged} \quad (13)$$

where the variances of the hedge portfolio are obtained from the variance of the rate of return $R_{H,t}$ and the variance of the unhedged portfolio is the variance of spot returns, $R_{s,t}$. Hedging method with a higher HE is regarded as a superior hedging strategy as when the HE increases, then it indicates a higher effectiveness and larger risk reduction.

4.0 DATA

This research used daily closing prices of spot, futures contract and three month forwards contract for the currencies within the ASEAN plus three (ASEAN+3) countries. Due to unavailable futures market in ASEAN market, we used forwards as a proxy for hedging instruments within the market. Futures market consists of the Japanese Yen (JPY), Korean Won (KRW), and China Yuan (CNY), while forwards market consists of Malaysia Ringgit (MYR), Singapore Dollar (SGD), and Philippine Peso (PHP). The spot and forwards exchange rates are obtained from Thomson Reuters (DataStream database), and futures exchange rate are downloaded from the Chicago Mercantile Exchange (CME), (DataStream database). For each currency, 2150 observations (after removing non-trading days) are collected starting from 18th September 2006 to 31st October 2014.

The returns of currency i at time t is calculated as $R_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the closing prices of currency i for days t, and $P_{i,t-1}$ is the closing prices of currency i for days $t-1$. Volatility can be observed from exchange rates spot, futures and forwards returns (Figure 1). Volatility refers to periods of high volatility followed by periods of relative tranquility. For example, Korean Won spot returns portrays turbulent periods (periods of high volatility) in 2008, and followed by periods of tranquility (volatility is low) from 2009 to 2014.

The mean return values for all series are close to zero (Table 1). The standard deviation observed in the range between 0.001026 and 0.0088, suggesting low volatility for each series. Besides that, it is found that the return series have high kurtosis, which is known as leptokurtosis, indicating that the distribution of returns are fat tailed. There were six series with positive skewness and six series with negative skewness. The positive skewness statistic signified the series had a longer right tail, suggesting that there were more gains than losses to investment returns, while negative skewness indicate more losses than gains. Under the null hypothesis of normal distribution, the Jarque-Bera statistic for each return series is tested to be significant at five percent (5%) level. It can be concluded that there is enough evidence to reject the null hypothesis of normal distribution. Hence, all spot, futures and forwards return series are concluded to be not normally distributed.

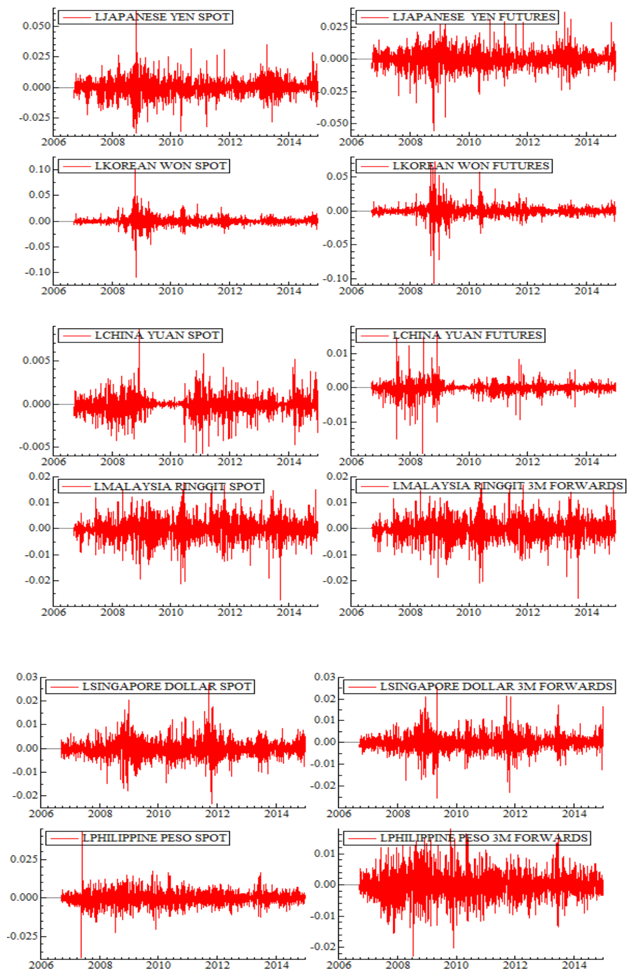


Figure 1 Spot, futures and forwards daily return

Table 1 Descriptive statistics of spot, futures, and forwards returns

Returns	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis	Jarque-Bera	Prob.	Sum	Sum Sq. Dev
Japanese Yen Spot	6.66E-06	0	0.062034	-0.03706	0.006948	0.154363	8.84719	3069.931	0.00	0.014305	0.103706
Japanese Yen Futures	7.07E-06	0	0.036894	-0.05543	0.006892	-0.37596	9.156487	3444.465	0.00	0.015193	0.102023
Korean Won Spot	6.25E-05	-5.53E-05	0.102163	-0.10945	0.008187	-0.08563	36.02791	97678.53	0.00	0.134328	0.143981
Korean Won Futures	6.31E-05	0	0.072224	-0.10719	0.0088	-0.41902	29.02504	60709.72	0.00	0.135525	0.166332
China Yuan Spot	0.00012	-1.63E-05	0.008614	-0.00569	0.001026	0.138509	9.183751	3430.835	0.00	-0.24724	0.002262
China Yuan Futures	0.00012	0	0.016461	-0.01927	0.001685	-0.27305	29.85732	6461.53	0.00	-0.25335	0.006097
Malaysia Ringgit Spot	-2.38E-05	0	0.017702	-0.02727	0.004083	-0.22169	6.032012	840.7678	0.00	-0.05115	0.035802
Malaysia Rinrgit 3M Forwards	-1.82E-05	0	0.017516	-0.02694	0.004048	-0.21058	5.998852	821.1416	0.00	-0.03908	0.035199
Singapore Dollar Spot	-8.36E-05	-0.00012	0.026635	-0.02321	0.003632	0.21009	8.066933	2314.685	0.00	-0.17960	0.028332
Singapore Dollar 3M Forwards	-8.14E-05	-0.00016	0.025203	-0.02554	0.003757	0.229616	9.202325	3463.447	0.00	-0.17493	0.030322
Philippine Peso Spot	-5.26E-05	0	0.043475	-0.03869	0.00434	0.171236	11.74873	6864.051	0.00	-0.11303	0.040463
Philippine Peso 3M Forwards	-5.28E-05	5.80E-05	0.017865	-0.02286	0.004309	0.056493	4.691081	257.2104	0.00	-0.11341	0.039886

5.0 RESULT AND DISCUSSION

The currency returns are found to be stationary using Augmented Dickey Fuller unit root test. Using the Ljung-Box and ARCH LM test, the result shows that there are autocorrelation and ARCH effects. Since we conclude there are ARCH effects, the research can proceed on using the GARCH model of CCC, DCC and Diagonal BEKK. Table 2 shows the estimation parameters for Constant Conditional Correlation (CCC) GARCH model. This model is assumed to have constant conditional correlation and the conditional correlation is time-varying. The ARCH (α) and GARCH (β) estimation of the conditional variances were statistically significant at five percent (5%) level. Korean Won and China Yuan are dropped since both currencies do not meet the assumptions of α + β is less than 1. The ARCH (α) estimations are generally small and observed between 0.044917 (Japanese Yen futures returns) and 0.114912(Malaysia Ringgit spot). The GARCH (β) effect is observed to be approaching one for each return series. Therefore, there is a strong GARCH effect and a weak ARCH effect.

The long run persistence in spot, futures and forwards returns are measured by the sum of ARCH (α) and GARCH (β). For each currency, the result shows significantly high volatility persistence, ranging from 0.97348 (MYR spot) to 0.99514 (¥ futures). This can be argued that high volatility persistence among ASEAN+3 countries would have a long memory process. The Dynamic Conditional Correlation (DCC) is an extension of the Conditional Correlation (CCC). This model is used to capture dynamic conditional correlations.

As tabulated in Table 3, the short run persistence of shocks is identified by theta one (θ_1), while the sum of theta one (θ_1) and theta two (θ_2) are used to identify the long run persistence of shock. The parameters show that theta one (θ_1) for all returns are statistically significant at five percent (5%) level. Meanwhile, theta two (θ_2) values for Japanese Yen, Malaysia Ringgit, and Philippine Peso returns are statistically significant at five percent (5%) level. Whenever significant occurs in return series, it can be argued that the conditional correlation is dynamic over time. The Philippine Peso shows the highest short run persistence with 0.136844 and greatest long run persistence with sum of theta one (θ_1) and theta two (θ_2) equal to 0.908959 (0.136844+0.772115).

Diagonal Baba, Engle, Kraft and Kroner (Diagonal-BEKK) is the alternative model for dynamic conditional correlation and guaranteed to have coefficient of ARCH and GARCH with positive definite on the conditional covariance 2 x 2 matrices. The conditional variances are depending on their own lags and lagged shock. However, it is the function of its lagged covariance and the lagged cross-products of the shocks. Japanese Yen, China Yuan, Malaysia Ringgit, and Singapore Dollar are statistically significant on both values of ARCH (A) and GARCH (B) effects, while Korean Won only significant for GARCH (B) (Table 4). Therefore, it can be concluded that there is a strong effect of GARCH ranging from 0.888512 to 0.968422 and a weak presence of ARCH effects ranging from 0.214816 to 0.4119247. Table 5 reports the values of optimal hedge ratio (OHR), the hedging effectiveness (HE), and the portfolio variance of four foreign exchange rates from three multivariate GARCH models, namely; Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC) and Diagonal-BEKK. Moreover, optimal hedge ratio (OHR) is defined by variance (second moment) of spot, futures and forwards returns. Therefore, the values of OHR will differ from one to another. OHR can be calculated as:

$$B_t^*|\varphi_{t-1} = cov(R_{s,t}R_{f,t}|\varphi_{t-1})/var(R_{f,t}|\varphi_{t-1}) \quad (14)$$

The optimal hedge ratio (OHR) for Japanese Yen is 0.77774653, 0.76263126, and 0.779831217 for BEKK, CCC and DCC respectively (Table 5). Malaysia Ringgit shows the OHR of 0.99204898 (BEKK), 0.99204852 (CCC), and 0.987445131 (DCC). Moving on to Philippine Peso, OHR are calculated at 0.956553745 (BEKK), 0.992722835 (CCC), and 0.963503105 (DCC). Finally, Singapore Dollar shows the OHR of 0.8129118 (BEKK), 0.790870197 (CCC), and 0.805751913 (DCC). It is found that the Philippines Peso has the highest optimal hedge ratio (OHR) of 0.99204898, and the lowest is Japanese Yen with OHR of 0.76263126 using the Constant Conditional Correlation (CCC) GARCH model.Hence, in order to minimize risk, the investment on long (buy) position of one unit of Japanese Yen spot should be hedged by short (sell) position of ¥ 0.7783 in futures contract. For Malaysia Ringgit, it is suggested that long (buy) position of one Ringgit spot should be hedged by short (sell) position of RM 0.9920 in forwards contract. On the other hand, the OHR for Singapore Dollar is 0.805751913 and it showed that the investor can long (buy) one Singapore Dollar spot and is shorted by S$ 0.8056 in forwards. The result also suggested that one Philippine Peso long (buy) in spot prices should be shorted (sold) by ₱ 0.9927 in forwards contract. Finally, this research revealed that best models for hedging effectiveness are CCC and DCC. These two models enable investors to reduce the variance up to 59.64 percent for Japanese Yen, 97.42 percent for Malaysia Ringgit, 66.14 percent for Singapore Dollar and 93.42 percent for Philippine Peso.

Table 2 CCC Estimates

Exchange Rates (Returns)	C	Ω	α	β	α + β	CCC	Log-likelihood	AIC	SIC
JAPANESE YEN SPOT	0.000185	0.697651	0.076277	0.912795	0.98907	0.765806	16832.892	-15.656484	-15.630087
JAPANESE YEN FUTURES	0.000136	0.320359	0.044917	0.950223	0.99514				
MALAYSIA RINGGIT SPOT	-0.000145	0.544288	0.114912	0.858565	0.97348	0.987865	21825.663	-20.303084	-20.276686
MALAYSIA RINGGIT 3M FORWARDS	-0.000135	0.493316	0.105669	0.869478	0.97515				
SINGAPORE DOLLAR SPOT	-0.000100	0.084524	0.055485	0.939068	0.99455	0.808995	19850.164	-18.464555	-18.438158
SINGAPORE DOLLAR 3M FORWARDS	-0.000106	0.127418	0.075789	0.918496	0.99429				
PHILIPPINE PESO SPOT	0.000004	0.325159	0.097603	0.892087	0.98969	0.985850	21432.294	-19.936989	-19.910592
PHILIPPINE PESO 3M FORWARDS	-0.000068	0.134318	0.058466	0.935769	0.99424				

Table 3 DCC estimates

Exchange Rates (Returns)	C	ω	α	β	α + β	θ_1	θ_2	Log-likelihood	AIC	SIC
JAPANESE YEN SPOT	0.000185	0.697651	0.076277	0.912795	0.98907	0.129576	0.246440	16865.226	-15.684715	-15.653039
JAPANESE YEN FUTURES	0.000136	0.320359	0.044917	0.950223	0.99514					
MALAYSIA RINGGIT SPOT	-0.000145	0.544288	0.114912	0.858565	0.97348	0.113716	0.759832	22310.818	-20.752739	-20.721062
MALAYSIA RINGGIT 3M FORWARDS	-0.000135	0.493316	0.105669	0.869478	0.97515					
SINGAPORE DOLLAR SPOT	-0.000100	0.084524	0.055485	0.939068	0.99455	0.130690	0.045148	19884.041	-18.494221	-18.462545
SINGAPORE DOLLAR 3M FORWARDS	-0.000106	0.127418	0.075789	0.918496	0.99429					
PHILIPPINE PESO SPOT	0.000004	0.325159	0.097603	0.892087	0.98969	0.136844	0.772115	21678.330	-20.164104	-20.132427
PHILIPPINE PESO 3M FORWARDS	-0.000068	0.134318	0.058466	0.935769	0.99424					

Table 4 BEKK estimates

Exchange Rates (Returns)	C	C		A		B		Log-likelihood	AIC	SIC
JAPANESE YEN SPOT	0.000097	0.001388		0.340834		0.930571		16857.616	-15.679493	-15.653096
JAPANESE YEN FUTURES	0.000140	0.001009	0		0.214816		0.968422			
KOREAN WON SPOT	-0.000219	0.001136		0.405564		0.914061		18230.732	-16.957405	-16.931008
KOREAN SPOT FUTURES	-0.000224	0.001146	0.000188		0.409334		0.912379			
CHINA YUAN SPOT	-0.000029	0.000070		0.390705		0.920511		24047.526	-22.370894	-22.344497
CHINA YUAN FUTURES	-0.000036	0.000066	0.000128		0.268790		0.952833			
MALAYSIA RINGGIT SPOT	-0.000062	0.001159		0.373108		0.927782		22387.039	-20.825537	-20.799140
MALAYSIA RINGGIT 3M FORWARDS	-0.000056	0.001192	0		0.380085		0.923978			
SINGAPORE DOLLAR SPOT	-0.000138	0.000894		0.411927		0.888512		19589.238	-18.222651	-18.198893
SINGAPORE DOLLAR 3M FORWARDS	-0.000138	0.000580	0.000001		0.285416		0.947301			
PHILIPPINE PESO SPOT	-0.000122	0.001552		0.461261		0.885535		22063.007	-20.523972	-20.497574
PHILIPPINE PESO 3M FORWARDS	-0.000115	0.001547	0.000095		0.463913		0.885875			

Table 5 Optimal hedge ratio and hedging effectiveness

		JAPANESE YEN	MALAYSIA RINGGIT	SINGAPORE DOLLAR	PHILIPPINE PESO
AVERAGE OPTIMAL HEDGE RATIO (OHR)	BEKK	0.77774653	0.99204898	0.8129118	0.956553745
	CCC	0.76263126	0.99204852	0.790870197	0.992722835
	DCC	0.779831217	0.987445131	0.805751913	0.963503105
VARIANCE PORTFOLIO	BEKK	2.81287E-05	7.06166E-07	5.50852E-06	2.81705E-06
	CCC	2.12866E-05	4.45663E-07	4.82942E-06	1.3226E-06
	DCC	2.02643E-05	5.52109E-07	4.54143E-06	0.00000221
VARIANCE UNHEDGED	BEKK	5.89083E-05	2.61931E-05	1.44906E-05	2.97453E-05
	CCC	5.02048E-05	1.73252E-05	1.34117E-05	2.01034E-05
	DCC	5.02048E-05	1.73252E-05	1.34117E-05	2.01034E-05
HEDGING EFFECTIVENESS (HE)	BEKK	52.25%	97.30%	61.99%	90.53%
	CCC	57.60%	97.43%.	63.99%	93.42%
	DCC	59.64%	96.81%	66.14%	89.00%

5.0 CONCLUSION

The hedging effectiveness of exchange rates within the ASEAN plus three (ASEAN+3) is investigated. It is found that the Philippine Peso has the highest average optimal hedge ratio (OHR) of 0.99204898, and the lowest is Japanese Yen with average OHR of 0.76263126 using the Constant Conditional Correlation (CCC) GARCH model. We can declare that the ASEAN currency markets are volatile. Hence, in order to minimize risk, the investment on long (buy) position of one unit of Japanese Yen spot should be hedged by short (sell) position of ¥ 0.7783 in futures contract. For Malaysia Ringgit, it is suggested that long (buy) position of one Ringgit spot should be hedged by short (sell) position of RM 0.9920 in forwards contract. On the other hand, the OHR for Singapore Dollar is 0.805751913 and it showed that the investor can long (buy) one Singapore Dollar spot and is shorted by S$ 0.8056 in forwards. The result also suggested that one Philippine Peso long (buy) in spot prices should be shorted (sold) by ₱ 0.9927 in forwards contract.

Finally, it is revealed that the best model for hedging effectiveness is found to be CCC and DCC multivariate GARCH models. These two models are able to reduce the variance 59.64 percent for Japanese Yen, 97.42 percent for Malaysia Ringgit, 66.14 percent for Singapore Dollar and 93.42 for Philippine Peso. Hence, it can be suggested to investors to hedge Malaysia Ringgit since the currency has the highest reduction in risk.

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