FORECASTING PORTFOLIO VALUE-AT-RISK FOR INTERNATIONAL STOCKS, BONDS AND FOREIGN EXCHANGE: EMERGING MARKET EVIDENCE

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Abstract

This paper uncovers the nature of conditional correlations between and volatility spillovers across bond, stock and foreign exchange in Indonesia, Malaysia, the Philippines, and Thailand. Using various multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, it finds the evidence of highly persistence in the conditional variance, volatility spillovers across assets, and time-varying conditional correlations in all markets. It also provides Value-at-Risk forecast based on the estimated models. Assuming normal distribution, the tests suggest that incorporating volatility spillovers and time-varying conditional correlations does not help in providing Value-at-Risk forecasts. Assuming t distribution, the tests suggest that incorporating volatility spillovers provides better VaR forecasts.

Keywords: *conditional correlations, volatility spillovers, VaR forecast*
JEL classification numbers: *F37, G11, G15*

INTRODUCTION

This paper intends to uncover the usefulness of volatility spillovers and time-varying conditional correlations in finance literature. Specifically, the paper aims to investigate the impact of incorporating volatility spill-overs and dynamic conditional correlations in multivariate GARCH models on Value-at-Risk (VaR) forecast.

VaR can be viewed as the latest step in the evolution of risk-management tools. It can summarize the worst portfolio loss related to the trading of financial assets over a given time period with a given level of confidence. Even though VaR should be viewed as a necessary but not sufficient condition procedure for controlling risk, it has been used as a standard tool for risk managers (see Jorion, 2001 for further discussion about VaR).

The development of univariate, and especially multivariate, GARCH-family models has contributed to the development of VaR forecasts methods. Three advantages of estimating multivariate GARCH models are the possibility of estimating the conditional covariances between assets, incorporating the interaction across those assets, and considering the conditional correlations across those assets. These might improve the VaR forecasts accuracy of a portfolio comprising these components, since the calculation of VaR of a portfolio requires the estimation of standard deviation and correlations across assets (see Skintzi et al., 2005).

Three assets are to be considered, namely stock, bond and foreign exchange. This paper considers four emerging markets,

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namely Indonesia, Malaysia, Philippine, and Thailand.

Four multivariate GARCH-type models to be considered are the Diagonal VEC (DVEC) model of Bollerslev et al. (1988), the Baba Engle Kraft and Kroner (BEKK) model of Engle and Kroner (1995), the Constant Conditional Correlation (CCC) model of Bollerslev (1990), and the Dynamic Conditional Correlation (DCC) model of Engle (2002). The BEKK model is estimated as it incorporates the volatility spillovers across assets. The DCC model will be estimated to incorporate time-varying conditional correlations across assets. The DVEC and CCC models serve the benchmarks as both models do not incorporate both volatility spillovers and time-varying conditional correlations. This paper estimates 6 portfolios, where each portfolio consists of 2 countries. Therefore, each portfolio contains 6 assets (2 bonds, 2 stocks and 2 foreign exchanges).

The paper considers various tests of Unconditional Coverage (CC) of Kupiec (1995) and Christoffersen (1998), the Conditional Coverage (CC) of Christoffersen (1998) and Lopez (1999), and Time Until First Failure (TUFF) of Kupiec (1995) regarding the violation of VaR resulted by the models. The UC test is uniformly most powerful for a given sample size (see Lopez, 1999). However, in the presence of time dependent heteroscedasticity, what is more important is the conditional accuracy of interval forecasts (see Lopez, 1999). This leads to the application of the CC test. Another type of test, the TUFF test, will also be applied. This test is important from the performance-based scheme (see Kupiec, 1995).

Investigating the impact of volatility spillover and conditional correlations on VaR forecasts in emerging assets are of interests for several reasons. As suggested by Bekaert and Harvey (1997), emerging market returns have higher average returns, more predictable returns, and higher volatility, compared with those of developed markets. They also have low correlations with developed market returns. In addition, as suggested by Hakim and McAleer (2008), the volatility spillovers from developed to emerging markets are stronger than those from emerging to developed markets. As a result, one can expect that portfolio consists of only emerging markets will be riskier than those contains both emerging and developed and emerging markets. This motivates the paper to find out the performance of VaR forecasts, as a measure of portfolio risk, resulted from the four estimated models.

The literature on VaR forecast in emerging markets is limited. Most of the available papers focus on stock markets. The literature in this paper will be classified with respect to the estimated models.

The RiskMetrics^{TM} - EWMA for calculating VaR thresholds has been applied by Bao et al. (2006), Chiu et al. (2006), Lin et al. (2006), and Yao et al. (2006). The EWMA models cannot outperform GARCH family models. However, Bao et al. (2006) find that EWMA performs reasonably well in tranquil periods. In addition, Lin et al. (2006), assuming generalized error distribution, show that EWMA offers substantial improvements on capturing returns distributions, and can significantly enhance the estimation accuracy of portfolio VaR.

The most popular parametric methods to foerecast VaR, namely GARCH family models, have been used by some papers. Univariate GARCH family models have been applied by Chiu et al. (2006), Yao et al. (2006), Bhattacharyya et al. (2008) and Cheong (2008). As in previous paragraph the univariate GARCH models outperform EWMA. In addition, Bhattacharyya et al. (2008) find that assuming Pearson's Type IV distribution is a much better fit as compared to normal distribution on the standardized residuals obtained from the GARCH models of log returns. However, Cheong (2008) finds that the predicted VaR under the Pareto distribution and long-memory ARCH are the same.

Multivariate GARCH models have been used to forecast VaR in emerging markets by Da Veigaet al., 2008a,b). Using VARMA-AGARCH model of McAleer et al. (2008), Da Veiga et al. (2008b) find that adjusting for the structural change may not be overly important. Da Veiga et al. (2008a) find that the DCC models perform better than the CCC model. So far, there is no papers estimate Stochastic Volatility family models to forecast VaR in emerging markets.

Among the semiparametric application of VaR methods, the EVT and Quantile Regression approaches are the most popular. Engle and Manganelli (2004) propose a CaViar model that estimate VaR by modeling the quantile directly. Bao et al. (2006) apply the EVT and CaViar model on Asian stock markets, namely Indonesia, Korea, Malaysia, Taiwan, and Thailand. They find that the EVT-based models do better in the crisis period. They also find that the CaViaR quantile regression model of Engle and Manganelli (2004) have shown some success in predicting the VaR risk measure for various periods, generally more stable than those that invert a distribution function.

Belongs to the nonparametric models for calculating VaR is the historical simulation (HS) model. Bao et al. (2006) apply the model to forecast VaR in Asian stock markets. They find that the HS model cannot outperform the other parametric models, namely the EVT-based models and the CaViaR models. Cheong (2008) applies nonparametric quantile estimation to forecast VaR of Malaysian stock markets. He finds that the nonparametric method cannot outperform ARCH type models.

Regarding the test to evaluate the VaR forecasts, most papers use unconditional and conditional coverage, and also the TUFF tests. Unconditional coverage has been used by Chiu et al. (2006), Lin et al. (2006), Yao et al. (2006) and Da Veiga et al. (2008a). Conditional coverage has been used by Chiu et al. (2006), Yao et al. (2006) and Da Veiga et al. (2008a). The TUFF test has been used by Da Veiga et al. (2008a).

METHODS

The data investigated in this paper are the daily closing price index of bonds, stocks, and foreign exchange rates from Indonesia, Malaysia, the Philippine, and Thailand. Only the exchange rates against USD are investigated. Therefore, there will be 12 series to be investigated, namely 4 bonds, 4 stocks and 4 exchange rates.

The observations are from 7/1/2003 to 18/6/2007, with 1160 observations for each asset. The returns of market i at time t are calculated as $R_{i,t} = 100 \times log(P_{i,t} / P_{i,t-1})$, where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and $t-1$, respectively. Table 1 lists the series. All the data are obtained from the Bloomberg and DataStream database services.

Stationarity is an important characteristic for time series data. If a time series is nonstationary, the underlying processes will be explosive so that the cointegration method should be used. Moreover, the conditional mean model may be inadequate for forecasting purposes. This section presents both the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests to examine the stationarity of the return series. Both tests include a drift and a trend. The motivation for using the PP test is to accommodate the possible presence of ARCH or GARCH errors. While the ADF test accommodates serial correlation by specifying explicitly the structure of serial correlation in the errors, the PP test does not assume the specific type of serial correlation or heteroscedasticity in the disturbances, and can have higher power than the ADF test under a wide range of circumstances (for further details, see Phillips and Perron, 1988). All returns are found to be stationary, based on both ADF and Phillips-Perron tests. The test results are available upon written request to the author. VaR at level α for returns y_t is the corresponding empirical quantile at (1-α). Because quantiles are direct functions of the variance in parametric models, GARCH-class models immediately translate into conditional VaR models.

For random variable y_t with the conditional variance follow univariate GARCH specification,

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_i \varepsilon_{i,t-l}^2 \sum_{l=1}^{s} \beta_i h_{i,t-l} \ , \tag{2}$$

the VaR threshold for y_t can be calculated as:

$$VaR_t = E(y_t | F_{t-1}) - z\sqrt{h_t} \ , \tag{3}$$

where z is the critical value from the distribution of ε_t to obtain the appropriate confidence level. Alternatively, h_t can be replaced by estimates of various GARCH-family models to obtain an appropriate VaR.

To investigate whether accommodating dynamic correlations among and interactions across assets in the conditional variance can improve the forecasts of VaR, four multivariate GARCH models will be estimated. The models are the DVEC models of Bollerlsev et al. (1988), the BEKK model of Engle and Kroner (1995), the CCC model of Bollerslev (1990), and the DCC model of Engle (2002).

Bollerslev et al. (1988) propose VEC model to model the covariance matrix of a multivariate GARCH model. The VEC model suffers from a common problem associated with multivariate GARCH models, namely the curse of dimensionality. The model also requires further parametric restrictions to ensure the positive definiteness of the estimated covariance matrix.

Table 1: Summary of Variables

No	Variable	Index Names	Variable Names
1	Indonesian Bond	Indonesian Govt. Bond (INDOGB 14.5 10)	Indbond
2	Malaysian Bond	Malaysian Govt. Bond (MGS 8.5 12)	Malbond
3	Philippines Bond	Philippine Govt. Bond (RPGB 14.75 10)	Phibond
4	Thailand Bond	Thailand Govt. Bond (THAIGB 4.125 8)	Thabond
5	Indonesian Stock	Jakarta SE Composite – Price Index	Indstock
6	Malaysian Stock	Kuala Lumpur Comp. DSCALC -Price Index	Malstock
7	Philippines Stock	Philippine SE I(PSEi) – Price Index	Phistock
8	Thailand Stock	DJSI World Thailand Subset - Price Index	Thastock
9	Exchange Rates	USD/IDR	Usdidr
10	Exchange Rates	USD/MUR	Usdmyr
11	Exchange Rates	USD/PHP	Usdphp
12	Exchange Rates	USD/THB	Usdthb

To reduce the number of parameters, Bollerslev et al. (1988) suggest the DVEC model. However, the model does not incorporate the volatility spillovers across assets. The BEKK model of Engle and Kroner (1995) resolves the positive definiteness issue and incorporates spillover effects; it did not resolve the problem associated with the curse of dimensionality.

These multivariate GARCH models focus on the dynamic of the conditional covariance matrix, whereas models such as the CCC model of Bollerslev (1990) and the DCC model of Engle (2002) focus on the dynamic of the conditional variances and the conditional correlation matrix.

The specification of the VEC model is:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \tag{4}$$

$$\varepsilon_t = D_t \eta_t \tag{5}$$

$$\begin{aligned} vech(H_t) = C + \sum_{i=1}^{q} A_i vech(\eta_{t-1}\eta_{t-1}^{'}) \\ + \sum_{j=1}^{p} B_j vech(H_{t-j}) \end{aligned} \tag{6}$$

where:
$y_t = (y_{1t},...,y_{mt})'$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$ is a sequence of identically and independently (i.i.d) random vectors, F_t is the past information available to time t, $D_t = diag(h_{1t}^{1/2},...,h_{mt}^{1/2})$, m is the number of returns, and $t = 1,...,n$, $H_t = (h_{1t},...,h_{mt})$, $vech(.)$ denotes the column stacking operator of the lower portion of a symmetric matrix, C is a $\frac{1}{2}N(N+1)\times 1$ vector, $A_i, i = 1,...,q$, and $B_j, j = 1,..., p$, are $\frac{1}{2}N(N+1)\times\frac{1}{2}N(N+1)$ matrices. The DVEC model is obtained by taking the main diagonal of matrices A and B in (6).

The CCC model of Bollerslev (1990) assumes that the conditional variance for each return, $h_{it}, i = 1,...,m$, follows a univariate GARCH process, namely

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} , \tag{7}$$

where α_{ij} represents the ARCH effect, or the short-run persistence of shocks to return i, and β_{ij} represents the GARCH effect, of the contribution of shocks to return i to long-run persistence, namely

$$\sum_{j=1}^{r} \alpha_{ij} + \sum_{j=1}^{s} \beta_{ij} < 1 . \tag{8}$$

The conditional correlation matrix of CCC is $\Gamma = E(\eta_t\eta_t^{'} | F_{t-1}) = E(\eta_t\eta_t^{'})$, where $\Gamma = \{\rho_{ij}\}$ for $i, j = 1,...,m$. From (5), $\varepsilon_t\varepsilon_t^{'} = D_t\eta_t\eta_t^{'}D_t$, $D_t = (diag Q_t)^{1/2}$, and $E(\varepsilon_t\varepsilon_t^{'} | F_{t-1}) = Q_t = D_t\Gamma D_t$ where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1}Q_tD_t^{-1}$, and each conditional correlation coefficient is estimated from the standardized residual in (4) and (7).

The conditional covariance of BEKK model can be written as follows:

$$Q_t = QQ' + A\varepsilon_{t-1}\varepsilon_{t-1}^{'}A' + BQ_{t-1}B' . \tag{9}$$

The DCC model is given by:

$$\begin{aligned} Z_t = (1-\theta_1-\theta_2)\overline{Z} + \theta_1\eta_{t-1}\eta_{t-1}^{'} \\ + \theta_2 Q_{t-1} \end{aligned} \tag{10}$$

$$\Gamma_t^{*} = \{(diag Z_t)^{-1/2}\} Z_t \{(diag Z_t)^{-1/2}\}, \tag{11}$$

where θ_1 and θ_2 are scalar parameters, and Z_t is the conditional correlation matrix after it is standardized by (11). For further detail about multivariate GARCH models, see McAleer (2005).

To evaluate the VaR forecasts accuracy, several back tests will be used, namely tests of unconditional coverage (UC), independence (IND), conditional coverage (CC), and time until first failure (TUFF). The UC test was first proposed by Kupiec (1995). The test examine whether the failure rate of a model is statistically different from expectation. Later Christoffersen (1998) derived likelihood ratio (LR) of UC, IND and CC.

In UC test, the probability of observing x violations in a sample of size T, is given by:

$$\Pr(x) = C_x^T (f)^x (1-f)^{T-x} \qquad (12)$$

where f is the desired proportion of observations. $C_x^T = \frac{T!}{x!(T-x)!}$ where ! denotes the factorial operator such that $T! = \prod_{i=0}^{T-1} T-i$. The null hypothesis is that the empirical failure rate, $\hat{f}$, is equal to the confidence level of the VaR, α. The LR statistic of UC is:

$$LR_{UC} = 2\log\left[\frac{(1-\alpha)^{n0}\alpha^{n1}}{(1-\hat{f})^{n0}\hat{f}^{n1}}\right], \qquad (13)$$

where $\hat{f} = x/T$, n_0 is the number of failures and n_1 is the number of success. The statistic is distributed as χ^2 with 1 degree of freedom.

The weakness of UC test is that it tests only the equality between the VaR violations and the confidence level. However, simply testing for the correct unconditional coverage is insufficient when dynamics are present in the higher-order moments. Therefore it is also important that the VaR violations are not correlated in time. The LR statistic of Christoffersen (1998) and Lopez (1999) for testing whether the series are independent is:

$$LR_{IND} = -2\log\left[\frac{(1-\hat{f})^{n_{00}+n_{10}}\hat{f}^{n_{01}+n_{11}}}{(1-\hat{f}_{01})^{n00}\hat{f}_{01}^{n01}(1-\hat{f}_{11})^{n10}\hat{f}_{11}^{n11}}\right], \qquad (14)$$

where n_{ij} is the number of observation with value i followed by j. The statistic is distributed as χ^2 with 1 degree of freedom.

The joint of unconditional coverage and independence tests are the conditional coverage test, with the following LR statistic:

$$LR_{CC} = LR_{UC} + LR_{IND}. \qquad (15)$$

The statistic is distributed as χ^2 with 2 degree of freedom.

The TUFF test of Kupiec (1995) is based on the number of observations until a failure is recorded, which is important in a performance-based verification scheme. The null hypothesis is the same as the UC test, namely the empirical failure rate, $\hat{f}$, is equal to the confidence level of the VaR, α. Given v, the number of days until the first failure occurs, it tests whether the underlying potential loss estimates are consistent with the null. Therefore, the null can be further set to $H_0 = \alpha = \hat{f} = 1/v$. The LR statistic, which follows χ^2 with 1 degree of freedom, is as follows:

$$LR_{TUFF} = -2\log\left[\hat{f}(1-\hat{f})^{v-1} \Big/ \frac{1}{v}\left(1-\frac{1}{v}\right)^{v-1}\right] \qquad (16)$$

RESULTS DISCUSSION

This section compares the forecasting performance of the models described in the introduction. For the purposes of empirical analysis, it is assumed that the portfolio weights are equal and constant over time, but this assumption can be relaxed. All the conditional volatility models are estimated under the assumption of normal and *t* distributions.

The evidence of volatility persistence and volatility spillovers across assets in the portfolios can be traced with the help of assets code number in each portfolio provided in Table 2. The code numbers are useful for such purposes as the tables that contain parameter estimates do not provide names of those assets, namely Tables 3 and 4 for the DVEC model, and Tables 5 and 6 for the CCC model. The estimation results of the BEKK model, which are 12 pages long, are not provided in this paper. The results are available upon written request to the author.

The estimated models are used to forecast 1-day-ahead 99% VaR thresholds, which is in line with the Basle Committee's recommendation. The sample is from 7/1/2003 to 18/6/2007, with 1160 observations for each index and foreign exchange rates. This constructs 1159 observations of return series. In order to strike a balance between efficiency in estimation and a viable number of forecasts, the sample size used for estimation is from 7/1/2003 to 31/1/2006 with 800 observations, and the forecasting period is from 1/2/2006 to 18/6/2007 with 359 observations. All estimations are conducted using the WinRATS 6.3 software package.

From 4 countries investigated, there are 6 portfolios to be considered, where each portfolio consists of pairs of countries. Each portfolio contains 6 assets, namely two bonds, two stocks and two foreign exchange rates. The estimation on the portfolio contain Usdmyr could not get the convergence. This might be due to the fact that Usdmyr is constant from the beginning of the observation until July 2005.[2] The convergence for these estimations is achieved after removing Usdmyr from the estimation. Therefore, the portfolios which contain Malaysia have only 5 assets. It can be informed that the parameter estimates and the corresponding *t* ratios provided by the BEKK models using normal and *t* distributions show that volatility spillovers are evident in most cases.

The estimate of parameters and the *t* ratios of the conditional variance from the DVEC model are provided in Tables 3 and 4 using normal and *t* distributions, respectively. The estimate of parameters and the *t* ratios of the conditional variance from the CCC model are depicted in Tables 5 and 6 using normal and *t* distributions, respectively. Both models, assuming both normal and *t* distributions, provide evidence of volatility persistence in most cases as well. There is also evidence of varying conditional correlations in all cases provided by the DCC model (see Table 7).

With 95% confidence levels, the critical value of chi-square for LR_{UC}, LR_{IND} and LR_{TUFF} is 3.84, while that of LR_{CC} is 5.99. The results from the UC, IND and CC tests assuming normal and *t* distributions are given in Tables 8 and 9, respectively. The test summary of the test results are provided in Table 10 for estimation assuming both normal and *t* distributions.

The test results suggest a mixture results. Assuming normal distribution, the UC test suggests that the BEKK and DCC models, both fail in 5 cases, perform worst than the DVEC and CCC models, both fail in 4 cases. This suggests that incorporating volatility spillovers and time-varying conditional

[2] Malaysian central bank switched its foreign exchange regime from the managed-float to the pegged system following the Asian financial crises in 1997. The system was switched back to the managed floating exchange rate in July 2005.

correlations does not help in providing VaR forecasts. The result of the CC test suggests similar results. The only different is that the CCC fails in 3 cases. The TUFF test does not provide much information, as all models do not fail the test, except the CCC model which fails in 1 case only.

Assuming *t* distribution, the UC test suggests that the BEKK model, fails in 3 cases, perform slightly better than the other models, which fail the test in 4 cases. This suggests that incorporating volatility spill-overs provides better VaR forecasts. The result of the CC and TUFF tests suggests exactly the same results.

Table 2: Code Number of Assets in Each Portfolio

No	Portfolio	Code Number					
		1	2	3	4	5	6
1	Ind-Mal	Indbond	Malbond	Indstock	Malstock	Usdidr	
2	Ind-Phi	Indbond	Phibond	Indstock	Phistock	Usdidr	Usdphp
3	Ind-Tha	Indbond	Thabond	Indstock	Thastock	Usdidr	Usdthb
4	Mal-Phi	Malbond	Phibond	Malstock	Phistock	Usdphp	
5	Mal-Tha	Malbond	Thabond	Malstock	Thastock	Usdthb	
6	Phi-Tha	Phibond	Thabond	Phistock	Thastock	Usdphp	Usdthb

Table 3: DVEC Estimation_Normal Distribution

	Ind-Mal		Ind-Phi		Ind-Tha		Mal-Phi		Mal-Tha		Phi-Tha	
	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t
C(1)	**0.04**	**2.29**	**0.04**	**2.34**	**0.04**	**2.50**	**0.01**	**2.51**	0.01	1.87	0.00	1.17
C(2)	**0.01**	**2.11**	0.00	1.38	0.01	1.64	0.00	1.17	**0.01**	**2.36**	**0.01**	**2.25**
C(3)	**0.20**	**3.00**	**0.20**	**2.54**	**0.22**	**2.96**	0.00	0.23	0.00	0.16	0.28	1.45
C(4)	0.00	0.26	0.26	1.81	**0.35**	**81.17**	0.27	1.76	4.82	1.88	**-0.01**	**-3012**
C(5)	**0.03**	**3.53**	**0.03**	**3.90**	**0.02**	**4.90**	0.00	1.19	0.01	1.81	**0.00**	**1.94**
C(6)			0.00	1.34	0.01	1.64					0.01	1.54
A(1)	**0.23**	**2.35**	**0.24**	**2.33**	**0.29**	**2.52**	**0.21**	**2.95**	**0.20**	**2.57**	**0.09**	**4.78**
A(2)	**0.20**	**3.16**	**0.09**	**4.21**	**0.10**	**2.92**	**0.09**	**3.72**	**0.10**	**2.60**	**0.10**	**3.82**
A(3)	**0.11**	**3.54**	**0.11**	**3.06**	**0.11**	**2.89**	0.02	0.80	0.02	0.98	**0.10**	**2.83**
A(4)	0.02	0.93	**0.10**	**2.62**	0.00	-0.05	**0.10**	**2.87**	**0.00**	**2.87**	0.00	-1.13
A(5)	**0.34**	**3.17**	**0.34**	**3.30**	**0.36**	**2.81**	**0.12**	**3.12**	**0.09**	**1.97**	**0.12**	**5.31**
A(6)			**0.12**	**2.91**	**0.09**	**2.08**					**0.09**	**2.09**
B(1)	**0.75**	**11.65**	**0.74**	**11.86**	**0.72**	**11.02**	**0.64**	**7.27**	**0.66**	**5.26**	**0.91**	**53.90**
B(2)	**0.64**	**6.21**	**0.91**	**46.15**	**0.84**	**14.77**	**0.91**	**46.14**	**0.85**	**20.72**	**0.85**	**26.06**
B(3)	**0.80**	**19.31**	**0.80**	**18.33**	**0.80**	**16.92**	**0.98**	**23.56**	**0.98**	**36.29**	**0.68**	**4.19**
B(4)	**0.98**	**29.19**	**0.69**	**4.96**	**0.89**	**645**	**0.69**	**4.78**	**-0.60**	**-3.67**	**1.00**	**905**
B(5)	**0.60**	**9.50**	**0.59**	**10.04**	**0.59**	**11.75**	**0.88**	**24.06**	**0.86**	**13.95**	**0.88**	**39.73**
B(6)			**0.88**	**21.56**	**0.86**	**13.31**					**0.86**	**13.50**

Notes: 1. The two entries for each parameter are its estimated coefficient and *t*-ratio, respectively.
2. Entries in **bold** are significant at the 5% level.

Table 4: DVEC Estimation_t Distribution

	Ind-Mal		Ind-Phi		Ind-Tha		Mal-Phi		Mal-Tha		Phi-Tha	
	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t
C(1)	**0.04**	**2.63**	**0.03**	**2.71**	**0.05**	**2.54**	0.00	1.19	0.00	1.11	0.00	1.10
C(2)	0.00	1.02	0.00	1.13	**0.01**	**2.07**	0.00	1.02	0.01	1.74	**0.01**	**3.05**
C(3)	**0.29**	**2.69**	**0.26**	**2.37**	0.43	1.72	0.01	0.53	0.02	1.12	**0.16**	**17.99**
C(4)	0.01	0.82	**0.29**	**2.50**	0.00	1.67	**0.23**	**2.21**	0.00	1.15	0.00	1.42
C(5)	**0.02**	**2.37**	**0.02**	**3.08**	**0.03**	**2.78**	0.00	1.67	0.00	1.84	0.00	1.22
C(6)			0.00	1.34	**0.01**	**2.17**					**0.00**	**3.11**
A(1)	**0.29**	**3.42**	**0.24**	**3.82**	**0.31**	**2.54**	**0.19**	**2.01**	0.34	1.73	**0.12**	**3.25**
A(2)	0.22	1.84	**0.15**	**3.25**	**0.17**	**3.72**	**0.11**	**3.42**	**0.12**	**2.76**	**0.09**	**4.67**
A(3)	0.08	1.63	**0.09**	**2.20**	0.12	1.75	0.05	1.16	**0.14**	**2.25**	**0.14**	**6.33**
A(4)	0.08	1.78	**0.20**	**3.72**	**0.46**	**16.50**	**0.17**	**3.67**	**0.34**	**3.60**	**0.26**	**4.78**
A(5)	**0.32**	**3.63**	**0.34**	**3.69**	**0.44**	**2.75**	**0.11**	**4.57**	**0.13**	**3.03**	**0.15**	**2.38**
A(6)			**0.14**	**3.01**	**0.17**	**4.01**					**0.10**	**4.61**
B(1)	**0.73**	**17.94**	**0.74**	**19.75**	**0.75**	**18.81**	**0.70**	**4.36**	**0.72**	**6.36**	**0.91**	**32.59**
B(2)	**0.78**	**6.90**	**0.89**	**30.95**	**0.86**	**32.59**	**0.90**	**36.27**	**0.88**	**23.72**	**0.88**	**48.56**
B(3)	**0.88**	**28.18**	**0.86**	**20.82**	**0.85**	**17.07**	**0.95**	**17.92**	**0.92**	**36.36**	**0.83**	**59.28**
B(4)	**0.95**	**32.41**	**0.73**	**9.51**	**0.80**	**32.73**	**0.75**	**10.47**	**0.84**	**37.46**	**0.82**	**31.31**
B(5)	**0.72**	**9.81**	**0.64**	**11.16**	**0.69**	**11.42**	**0.89**	**37.19**	**0.88**	**32.29**	**0.87**	**15.65**
B(6)			**0.89**	**28.88**	**0.86**	**38.54**					**0.87**	**36.38**

Notes: 1. The two entries for each parameter are its estimated coefficient and *t*-ratio, respectively.
2. Entries in **bold** are significant at the 5% level.

Table 5: CCC Estimation_Normal Distribution

	Ind-Mal		Ind-Phi		Ind-Tha		Mal-Phi		Mal-Tha		Phi-Tha	
	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t
C(1)	**0.03**	**1.98**	0.03	1.87	**0.02**	**2.37**	**0.01**	**2.66**	**0.01**	**8.30**	0.00	1.54
C(2)	**0.01**	**2.08**	0.00	1.63	0.00	1.51	0.00	1.46	0.00	1.73	0.00	1.79
C(3)	**0.21**	**3.41**	**0.18**	**3.10**	**0.21**	**2.75**	0.00	0.30	0.00	0.23	0.24	1.55
C(4)	0.00	0.19	0.19	1.27	0.02	1.44	0.24	1.66	**2.81**	**8.83**	0.24	1.24
C(5)	**0.03**	**3.99**	**0.03**	**3.41**	**0.02**	**4.26**	**0.00**	**2.11**	**0.00**	**1.99**	**0.00**	**2.44**
C(6)			**0.00**	**2.19**	**0.00**	**1.93**					**0.00**	**2.19**
A(1)	**0.26**	**2.74**	**0.27**	**2.36**	**0.37**	**2.56**	**0.21**	**2.89**	**0.20**	**2.37**	**0.12**	**3.39**
A(2)	**0.20**	**2.92**	**0.12**	**3.36**	**0.13**	**2.56**	**0.13**	**3.03**	**0.12**	**2.99**	**0.12**	**3.11**
A(3)	**0.11**	**2.82**	**0.12**	**3.27**	**0.10**	**2.99**	0.02	0.89	**0.02**	**6.36**	**0.10**	**2.38**
A(4)	0.02	0.59	**0.10**	**2.13**	2.27	1.59	**0.11**	**2.36**	**0.00**	**-6.82**	12.66	1.88
A(5)	**0.29**	**3.97**	**0.30**	**3.93**	**0.32**	**4.09**	**0.11**	**4.01**	**0.09**	**3.17**	**0.12**	**4.10**
A(6)			**0.11**	**3.63**	**0.11**	**2.72**					**0.10**	**3.10**
B(1)	**0.75**	**18.21**	**0.75**	**14.83**	**0.72**	**15.36**	**0.62**	**6.63**	**0.66**	**11.78**	**0.87**	**23.49**
B(2)	**0.65**	**6.12**	**0.87**	**27.33**	**0.85**	**19.61**	**0.87**	**21.24**	**0.87**	**22.59**	**0.87**	**27.24**
B(3)	**0.80**	**18.44**	**0.81**	**20.19**	**0.80**	**17.04**	**0.98**	**28.48**	**0.98**	**220.31**	**0.71**	**4.86**
B(4)	**0.98**	**19.29**	**0.75**	**4.91**	**0.44**	**6.30**	**0.71**	**5.25**	0.07	0.12	0.00	0.23
B(5)	**0.63**	**12.60**	**0.62**	**11.56**	**0.63**	**14.97**	**0.87**	**25.92**	**0.88**	**21.53**	**0.86**	**26.35**
B(6)			**0.87**	**26.92**	**0.86**	**18.81**					**0.87**	**24.44**

Notes: 1. The two entries for each parameter are its estimated coefficient and *t*-ratio, respectively.
2. Entries in **bold** are significant at the 5% level.

Table 6: CCC Estimation_t Distribution

	Ind-Mal		Ind-Phi		Ind-Tha		Mal-Phi		Mal-Tha		Phi-Tha	
	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t	Coeff	t
C(1)	**0.05**	**2.98**	**0.04**	**4.47**	**0.05**	**5.15**	**0.00**	**2.12**	0.00	1.26	**0.00**	**3.06**
C(2)	0.00	1.21	**0.00**	**2.60**	**0.01**	**6.51**	0.00	1.63	**0.01**	**2.01**	**0.01**	**7.45**
C(3)	**0.31**	**2.33**	**0.27**	**3.11**	**0.40**	**6.93**	0.01	0.60	0.01	0.41	**0.14**	**3.90**
C(4)	0.02	1.69	**0.30**	**1.97**	0.00	1.28	**0.24**	**2.76**	0.00	1.20	0.00	1.38
C(5)	**0.04**	**3.07**	**0.04**	**4.52**	**0.04**	**4.28**	0.00	1.72	**0.01**	**2.35**	**0.00**	**4.19**
C(6)			**0.00**	**2.53**	**0.01**	**9.94**					**0.01**	**7.59**
A(1)	**0.33**	**3.41**	**0.28**	**5.82**	**0.34**	**5.26**	**0.20**	**2.31**	0.27	1.73	**0.13**	**4.45**
A(2)	0.27	1.50	**0.20**	**4.49**	**0.17**	**8.30**	**0.13**	**3.56**	**0.12**	**2.76**	**0.11**	**7.65**
A(3)	0.08	1.60	**0.08**	**3.30**	**0.09**	**2.23**	0.04	1.13	0.08	0.77	**0.13**	**13.57**
A(4)	**0.09**	**2.18**	**0.22**	**5.42**	**0.42**	**4.36**	**0.16**	**3.10**	**0.31**	**4.62**	**0.29**	**4.54**
A(5)	**0.37**	**3.54**	**0.35**	**6.48**	**0.41**	**5.36**	**0.12**	**3.28**	**0.13**	**2.75**	**0.14**	**5.12**
A(6)			**0.18**	**4.14**	**0.18**	**9.54**					**0.11**	**6.86**
B(1)	**0.70**	**14.67**	**0.69**	**16.88**	**0.71**	**43.13**	**0.66**	**7.55**	**0.70**	**4.81**	**0.88**	**38.29**
B(2)	**0.74**	**6.64**	**0.86**	**29.15**	**0.87**	**54.66**	**0.87**	**24.59**	**0.89**	**32.07**	**0.88**	**70.53**
B(3)	**0.89**	**29.02**	**0.87**	**21.76**	**0.85**	**30.83**	**0.95**	**16.41**	**0.94**	**9.76**	**0.84**	**31.24**
B(4)	**0.94**	**99.50**	**0.74**	**8.42**	**0.83**	**31.75**	**0.75**	**12.81**	**0.83**	**35.26**	**0.82**	**27.31**
B(5)	**0.69**	**11.35**	**0.64**	**12.67**	**0.69**	**23.21**	**0.88**	**22.75**	**0.88**	**31.73**	**0.87**	**41.17**
B(6)			**0.87**	**26.82**	**0.86**	**57.59**					**0.87**	**82.92**

Notes: 1. The two entries for each parameter are its estimated coefficient and *t*-ratio..
2. Entries in **bold** are significant at the 5% level.

Table 7: DCC Model: Coefficients of Conditional Correlation Equation

No	Pairs of Countries	Normal Distribution		*t* Distribution	
		θ_1	θ_2	θ_1	θ_2
1	Indonesia-Malaysia	0.019	**0.965**	0.021	**0.891**
		1.721	**61.703**	1.860	**13.070**
2	Indonesia-Philippine	**0.022**	**0.957**	**0.025**	**0.959**
		4.884	**65.068**	**6.807**	**140.470**
3	Indonesia-Thailand	**0.053**	0.168	**0.052**	**0.948**
		2.058	1.056	**2119.954**	**38493.541**
4	Malaysia-Philippine	**0.021**	**0.942**	**0.020**	**0.951**
		7.352	**70.846**	**4.790**	**63.153**
5	Malaysia-Thailand	**0.038**	**0.956**	**0.057**	**0.942**
		12.401	**267.691**	**1017.069**	**18479.994**
6	Philippine-Thailand	**0.032**	**0.954**	**0.046**	**0.954**
		4.046	**75.771**	**1786.540**	**37096.166**

Notes: 1. Entries in **bold** are significant at the 5% level.
2. Entries in brackets are the corresponding *t* ratios of the coefficients.

Table 8: Tests of VaR Thresholds: Normal Distribution

No	Pairs of Countries	Models	Number of Violations	Number of observa-tions until the first failure	LR_{UC}	LR_{IND}	LR_{CC}	TUFF
1	Indonesia-Malaysia	BEKK	17	73	**26.565**	**9.996**	**36.560**	2.519
		DVEC	10	73	**7.785**	**5.830**	**13.615**	0.662
		CCC	11	73	**9.970**	**5.730**	**15.700**	0.885
		DCC	10	73	**7.785**	**5.830**	**13.615**	0.662
2	Indonesia-Philippine	BEKK	11	73	**9.970**	0.696	**10.665**	0.885
		DVEC	9	73	**5.806**	0.463	**6.269**	0.461
		CCC	9	73	**5.806**	0.463	**6.269**	0.461
		DCC	9	73	**5.806**	0.463	**6.269**	0.461
3	Indonesia-Thailand	BEKK	7	73	2.561	0.278	2.840	0.143
		DVEC	5	73	0.498	0.141	0.640	0.000
		CCC	4	5	0.046	0.090	0.136	**4.080**
		DCC	8	73	**4.056**	0.365	**4.420**	0.286
4	Malaysia-Philippine	BEKK	9	73	**5.806**	0.463	6.269	0.461
		DVEC	4	76	0.046	0.090	0.136	0.026
		CCC	3	76	0.104	0.051	0.154	0.180
		DCC	2	76	0.847	0.022	0.869	0.570
5	Malaysia-Thailand	BEKK	10	73	**7.785**	0.573	**8.358**	0.662
		DVEC	10	73	**7.785**	0.573	**8.358**	0.662
		CCC	10	73	**7.785**	0.573	**8.358**	0.662
		DCC	9	73	**5.806**	0.463	**6.269**	0.461
6	Philippine-Thailand	BEKK	12	69	**12.343**	**5.663**	**18.006**	0.967
		DVEC	11	73	**9.970**	0.696	**10.665**	0.885
		CCC	8	5	**4.056**	0.365	4.420	2.784
		DCC	8	73	**4.056**	**6.145**	**10.201**	0.286

Note: Entries in**bold** are significant at the 5% significance level.

CONCLUSSIONS

This paper investigated the nature of conditional correlations between and volatility spillovers across financial assets. Three assets were considered, namely bond, stock and foreign exchange. Four emerging countries, namely Indonesia, Malaysia, the Philippine, and Thailand, were analyzed. Four multivariate GARCH type models were estimated, namely the BEKK model of Engle and Kroner (1995), the DVEC model of Bollerslev et al. (1998), the CCC model of Bollerslev (1990), and the DCC model of Engle (2002). The estimates of DVEC and CCC parameters provided the evidence of highly persistence in the conditional variance. The estimates of the BEKK model provided evidence of volatility spillovers across assets. The estimates of the DCC model provided evidence of time-varying conditional correlations in all markets.

The paper also provided 1-day-ahead VaR forecast based on the estimated models. The test on the forecasts suggests a mixture results. Assuming normal distribution, the tests suggest that incorporating volatility spillovers and time-varying conditional correlations does not help in providing VaR forecasts. Assuming *t* distribution, the tests suggests that the BEKK model perform slightly better than the other models. This suggests that incorporating volatility spillovers provides better VaR forecasts.

Table 9: Tests of VaR Thresholds: *t* Distribution

No	Pairs of Countries	Models	Number of Violations	Number of observations until the first failure	LR_{UC}	LR_{IND}	LR_{CC}	TUFF
1	Indonesia-Malaysia	BEKK	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DVEC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		CCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
2	Indonesia-Philippine	BEKK	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DVEC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		CCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
3	Indonesia-Thailand	BEKK	2	73	0.847	0.022	0.869	0.618
		DVEC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		CCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
4	Malaysia-Philippine	BEKK	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DVEC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		CCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
		DCC	0	0	**7.216**	0.000	**7.216**	**#NUM!**
5	Malaysia-Thailand	BEKK	1	229	2.643	0.006	2.648	0.176
		DVEC	1	229	2.643	0.006	2.648	0.176
		CCC	1	229	2.643	0.006	2.648	0.176
		DCC	1	229	2.643	0.006	2.648	0.176
6	Philippine-Thailand	BEKK	2	73	0.847	0.022	0.869	0.618
		DVEC	1	229	2.643	0.006	2.648	0.176
		CCC	1	229	2.643	0.006	2.648	0.176
		DCC	1	229	2.643	0.006	2.648	0.176

Notes: 1. Entries in **bold** are significant at the 5% significance level.
2. #NUM! are entries that are failed to calculate due to zero violation.

Table 10: Test Summary

	UC Test		IND Test		CC Test		TUFF Test	
	Normal	t	Normal	t	Normal	t	Normal	t
BEKK	5	3	2	0	5	3	0	3
DVEC	4	4	1	0	4	4	0	4
CCC	4	4	1	0	3	4	1	4
DCC	5	4	2	0	5	4	0	4

Note: Entries are number the test failure.

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