Forecasting Time-Varying Correlation using the Dynamic Conditional Correlation (DCC) Model

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2014

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ABSTRACT

Hedging strategies have become more and more complicated as assets being traded have become more interrelated to each other. Thus, the estimation of risks for optimal hedging does not involve only the quantification of individual volatilities but also include their pairwise correlations. Therefore a model to capture the dynamic relationships is necessary to estimate and forecast correlations of returns through time. Engle's dynamic conditional correlation (DCC) model is compared with other models of correlation. Performance of the correlation models are evaluated in this paper using only the daily log returns of the closing prices of the Peso-Dollar Exchange Rate and Philippine Stock Exchange index. Ultimately, Engle's DCC model is adopted because of its consistency with expectations. Though generally negative, correlation between these two returns is not really constant as the results indicated. The forecast evaluation of the models was divided into in-sample and out-of-sample forecast performance with short-term (i.e., 22-day, 60-day, and 125-day) and medium-term (250-day and 500-day) rolling window correlations, or realized correlations, as proxies for the actual correlation. Based on the root mean squared error and mean absolute error, the integrated DCC model showed optimal forecast performance for the in-sample correlation patterns while the mean-reverting DCC model had the most desirable forecast properties for dynamic long-run forecasts. Also, the Diebold-Mariano tests showed that the integrated DCC has greater predictive accuracy in terms of the 3-month realized correlations than the rest of the models.

Keywords: dynamic conditional correlation, Peso-Dollar exchange rate, PSE index, hedging

I. Introduction

Correlations are vital inputs for many of the tasks of financial risk management. Forecasts of future correlations and volatilities are the basis of any pricing formula for financial instruments or strategy that would aid an investor or a company in mitigating unnecessary risks. Thus, it has been a tale of the tape to efficiently and accurately forecast financial correlations for risk planning and policy-making purposes. Several models have already been developed to capture the correlation pattern of financial time series. Some of the most common models are the constant conditional correlation model, the diagonal VECH model, and the diagonal BEKK model, which are multivariate GARCH methods readily estimated in latest versions of most software packages. However, Engle (2001) proposed a model that addresses the structural and empirical weaknesses of the latter models and attempts to accurately and parsimoniously pin down the dynamic pattern of the correlation which is why it is aptly name as the dynamic conditional correlation (DCC) model. This paper aims to assess the performance of the DCC model in forecasting the correlations between the returns of two Philippine financial series – the Philippine Stock Exchange Index (PSEi) and the nominal Peso-Dollar exchange rate– and see how the results compare with other correlation models.

Philippine Financial Markets

Investors from all over the world face the constant fear of losing their investments in just a single sweep mainly due to the sudden drops of the price levels of the market they're investing in. In the Philippines, two of the main financial markets are the equity markets and the foreign exchange markets. These institutions allow people to pool in their money in an investment, expecting that it will appreciate in value. However, economic theory suggests that the price levels of these assets across time are likely to be governed by certain phenomena. In the foreign exchange markets for example, movements in the levels of the nominal Peso-Dollar exchange rate are mainly determined by changes in the supply and demand for both currencies which can then be brought about by changes in consumer tastes, relative income, relative price level changes, relative interest rates, speculative activities, and domestic and foreign news. On the other hand, the equity market levels are very much affected by the expected earnings of the company and the expected dividends and returns of the stock. However, times of crises and recessions can bring panic and distress to most investors as shocks in the economy can greatly move the levels of almost all financial markets.

It is generally regarded that all risks should be avoided since it can cause much uncertainty and trouble in any financial arrangement. However, if the investor can precisely pinpoint the direction and magnitude of movements in price levels, say of the PSEi or the Peso-Dollar exchange rate, then the investor can make a position that can be rewarding for his or her part. However, this strategy takes on the risks of sudden changes in markets due to misguided expectations or a misspecification of a forecasting method. Moreover, it would be desirable for investors to enter into risky investments but be protected from the possible pitfalls at the same time.

Hedging Problem

One way that investors and institutions can manage the risks they're entering is through hedging, that is entering into another transaction whose sensitivity to fluctuations in prices counterbalances the sensitivity of their main transaction to such variations. A common hedging strategy is optimization of portfolio allocation. This entails minimizing the variance of the portfolio as it measures the level of risk of a pool of investments. The variance of a given portfolio is a function of the individual variability of each investment and their correlations with each other. Another hedging strategy commonly employed is the use of derivatives. Derivatives are basically contracts that are valued based on the price of other assets. They protect the holder of the contract by giving a payoff once a stipulated event occurs, usually a significant drop of the price level relevant to the main transaction, at a specific point of time. This protection however, comes with a premium to be paid at the commencement of the derivative, thus this financial instrument are almost synonymous with insurance.

An important hedging problem that arisesinvolving the PSE Index and the Peso-Dollar exchange rate is usually encountered by a foreign investor wishing to buy shares in the Philippines using a US Dollar currency. In entering such a transaction, the investor not only exposes himself to the risk of a sudden decline in the level of the PSEi but also exposes himself to the risk of the Dollar depreciating against the Peso. An equity-linked forward, called a quanto or a quantity adjusting option, is a derivative instrument that is designed to give a Dollar payoff if the overall Dollar value of the investment, that is the quotient of the PSE index and the Peso-Dollar exchange rate times the number of shares purchased, at the end of the quanto's expiration is less than some predetermined level. Although the original investment did not merit a profit, the investor was able to insure himself for the possible downfall. However, a seller determining a fair price for the quanto involves information on several financial parameters such as volatilities, interest rates, exchange rates, and most importantly, the correlation between the PSE index and the Peso-Dollar exchange rate.

Economics of Correlations

Movements in the levels of financial series such as the PSEi and the Peso-Dollar exchange rate are very much determined by internal and external news that are relevant to them. This news includes government policy implementations, interventions in markets, inside information, and recessionary movements. Prices of assets constantly change in response to news and in anticipation of future performance. Moreover, if news affecting both assets are correlated, then the prices of these assets will also be correlated. Then, both the volatilities of and correlations between asset returns or prices will depend on the information to update their distribution (Samuelson, 1965). Because of the existence of this correlation, one can generally dictate how the price or return of an asset will move based on the movement of the other asset. However, the nature of the news that affect both assets also vary across time. Thus, it is proper to think that the correlations between these assets are also varying across time. It should also be noted that forward-looking correlations are considered more important for an investor as this will dictate how the investment should be structured so that expected future payoffs will be realized. Thus, it might be of advantageous to investors if accurate long-term correlations could be forecasted so that proper strategies can be employed.

Though it is hypothesized that the correlations between financial series are time varying, several economic theories are proposed to give a general idea of the nature of these correlations. Macroeconomic theory suggests that in a healthy economic outlook, it is expected to have high equity levels and an appreciating currency, controlling for other variables. Cappiello and De Santis (2005) postulates the uncovered equity return parity condition which states that a country with a lower expected equity return will have an appreciating currency with respect to the country with a higher expected equity return.

Forecasting Correlations

In order to quantitatively capture the time-varying correlations between asset returns, several statistical models have been proposed various literatures. First and foremost, the parameters of interest are denoted as:

$\boldsymbol{H}_t = V(\boldsymbol{r}_t|\boldsymbol{I}_{t-1}) = \begin{bmatrix} h_{1,1,t} & h_{1,2,t} \\ h_{1,2,t} & h_{2,2,t} \end{bmatrix}$ the conditional covariance of two asset returns at time *t*

$\boldsymbol{R}_t = \boldsymbol{D}_t^{-1}\boldsymbol{H}_t\boldsymbol{D}_t^{-1}, \boldsymbol{D}_t^2 = diag(\boldsymbol{H}_t)$ the conditional correlation matrix of two asset returns at time *t*

The Constant Conditional Correlation model (Bollerslev, 1990) is a class of multivariate GARCH models which restricts the correlation matrix to be time invariant such that $\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}\boldsymbol{D}_t$. Though the estimation is simple, one major drawback is that nothing much can be learned about the dynamics of the correlations while assuming they are constant, though some studies have pointed out a constant correlation pattern in some short-term periods. A more popular class of multivariate GARCH models is the diagonal multivariate GARCH or diagonal vector GARCH (diagonal VECH) which formulates the i, j element of the covariance matrix as the product of the prior i and j returns (Bollerslev, Engle, & Wooldridge, 1988). The first-order diagonal VECH model is given by:

$$h_{i,j,t} = \omega_{i,j} + \alpha_i\alpha_j r_{i,t-1}r_{j,t-1} + \beta_i\beta_j h_{i,j,t-1}$$

However, the diagonal VECH model does not guarantee the positive definiteness of the resulting covariance matrices. The diagonal vector GARCH model was eventually modified to guarantee positive semi-definiteness of the covariance matrices by imposing a simple restriction for all the α's to be the same and all the β's to be the same, and requires that the matrix containing the elements $\omega_{i,j}$ to be positive definite. The model is called the diagonal BEKK vector GARCH model (Engle & Kroner, 1995) and it is given by:

$$h_{i,j,t} = \omega_{i,j} + \alpha r_{i,t-1}r_{j,t-1} + \beta h_{i,j,t-1}$$

It should be noted that for the diagonal VECH and diagonal BEKK models, the model specifies the dynamic pattern of the covariances, not the correlations, though they can be computed as an ad hoc procedure.

A model that directly estimates the conditional correlation is the dynamic conditional correlation model (Engle, 2002).This model formulates the volatilities of returns in one set of equations and the correlations between them in another set thus, treating them as independent stochastic processes, entailing more flexibility and different parameterizations. From the Monte Carlo simulations and real data context applications of the DCC model, it yielded the smallest mean absolute error among the vector GARCH and vector BEKK models, pinning much promise as to the quality of the results and simplicity of the method.

Many authors have used the DCC model to investigate the correlations of several macroeconomic variables. Bautista (2003) used the model to analyze the dynamic relationship between interest rate and exchange rate in the Philippines and saw that the correlations are mainly due to the effects of policies to exogenous events. Also, Vargas (2008) used a DCC model with an exogenous predictor to determine the key drivers of correlations between equity returns and exchange rate in select countries in Europe. Results show that interest rate differentials and capital flows were significant in explaining correlations between equity returns and exchange rate.

Significance and Limitations of the Study

One of the major motivations of this paper is that the correlations between assets are not constant through time. Testing data for constant correlation has proven to be a dilemma, as testing for dynamic correlation with data that have time-varying volatilities can result in misleading conclusions and lead to rejecting constant correlation when it is true due to incorrectly specified volatility models. This test only requires a consistent estimate of the constant conditional correlation, and can be implemented using a vector autoregression.

The dynamic conditional correlation model is a relatively new technique in modeling dynamic correlations. Thus, this model is not yet commonly employed in the business sector and other related fields in the Philippines. With this concern, it would be very invaluable if this model would be presented so that its features would be appreciated by many financial analysts.

Due to the lack of access to previous data because the Manila Stock Exchange started the computerization of its operations and production of a One Price-One Market Exchange only in 1994 and fully implementing it during the third quarter of 2006, the researchers used the PSEi data from 2000-2010 to acquire a sufficient number of data points in a time series analysis.

Descriptive Analysis of Data

Daily data of the Philippine stock exchange index closing price and the Peso-Dollar exchange rate were used in the analysis. The PSEi data was obtained from Yahoo! Finance as provided by Commodity Systems, Inc., while the exchange rate data was taken from the *Bangko Sentral ng Pilipinas*.

Both time series were cleaned to have matching dates, which range from July 2, 1997 to February 26, 2010. The result is an irregular time series with 3,116 observations. However, the estimation period started from January 3, 2000 because of the irregular patterns of the series during the 1998 Asian crisis and so these observations were excluded from the analysis, leaving 2213 observations.

The analysis of the models was divided into in-sample and out-of-sample. The data that was used for the in-sample was from January 3, 2000 to December 24, 2008 while the out-of-sample consisted of the data from January 5, 2009 to February 26, 2010.

The data was divided in this manner because this was the time of the inception of the global financial crisis's effects in the Philippines. The 2008 global economic and financial crisis spawned a synchronized recession among industrialized countries leading to a contraction in world trade. Exports from developing countries fell sharply dragging many of them into the global economic downturn. The Philippines was not spared the fallout from the crisis as GDP growth decelerated considerably in the fourth quarter of 2008 and first half of 2009. Asset prices experienced volatility but unlike the 1997 East Asian crisis, the financial sector remained fairly stable. It is also the time when remittances from overseas Filipino workers continued to grow, however, albeit at a lower rate. Foreign exchange reserves therefore maintained an upward trend despite the fall in exports and larger capital outflows. A cause of concern is the widening fiscal deficit, which is largely due to the need to increase government expenditures to offset lower consumption, investment, and exports. The Economic Resiliency Plan is a key component of the

Government response to the crisis. The exchange rate also exhibited volatility with the Peso depreciating by 16.6 percent between March 1, 2008 and November 30, 2008 after appreciating by 39 percent against the US dollar between September 20, 2005 and February 29, 2008. Between July 2008 and January 2009—which is the relevant period for monitoring the immediate impact of the financial crisis—the Peso depreciated by only 3. Similar to stock prices the Peso was one of the currencies least affected by the crisis. Much could be learned from the model due to this partitioning of the data. This could also assess the adequacy of the model if the results from the forecasted out-of-sample jive with the general trend of the correlations.

The Dynamic Conditional Correlation Model

The DCC was used to model the time-varying correlations between the returns of the PSEi and the exchange rate. This model is commonly used to understand changes in correlations in asset returns by treating them as random processes. In this model, the correlation estimates are updated every time new information on volatility-adjusted returns arrives (Engle, 2002).

The first-difference of the logarithm of the prices of each asset was taken to extract the log returns of the PSEi and exchange rate. The DCC model requires the standardized residuals from the mean-variance specification of each return series. For stationary return series, the autoregressive moving average (ARMA) models can be used to model the mean while the generalized autoregressive conditional heteroskedasticity (GARCH) models can be used to capture the time-varying volatilities of each return series. To check whether there is a leverage effect on the volatilities of either series, a Threshold GARCH (TGARCH) model can be estimated. But first, stationarity of the return series should be tested using the Dickey-Fuller GLS (ERS) test of unit root before proceeding to the joint estimation of the ARMA-GARCH models.

After the estimation of the mean variance specification, the standardized residualof the i^{th} asset at time *t* is given by the formula:

$$\varepsilon_{i,t} = \frac{r_{i,t} - \hat{r}_{i,t}}{\sqrt{h_{i,t}}}$$

where $r_{i,t}$ is the actual return, $\hat{r}_{i,t}$ is the estimated mean return using the ARMA model, and $h_{i,t}$ is the estimated conditional variance using the GARCH model. The elements of the standardized residual vector, $\boldsymbol{\varepsilon}_t$ for both the series is given by $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$.

For this study, two versions of the DCC model are used. Under the assumption that the changes in the correlations are mean-reverting and temporary, the mean-reverting DCC model is employed. First, a matrix $\boldsymbol{Q}_t$, called the quasi-correlation matrix, is postulated by the following specification:

$$\boldsymbol{Q}_t = \boldsymbol{\Omega} + \alpha \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} + \beta \boldsymbol{Q}_{t-1}$$

To save up on the parameters in estimating the intercept matrix, correlation targeting is used to estimate the intercept parameters. The intercept estimate using correlation targeting is given by:

$$\widehat{\boldsymbol{\Omega}} = (1 - \alpha - \beta)\overline{\boldsymbol{R}}, \quad \overline{\boldsymbol{R}} = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t$$

The new form of the mean-reverting DCC model is then given by:

$$\boldsymbol{Q}_t = \overline{\boldsymbol{R}} + \alpha(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} - \overline{\boldsymbol{R}}) + \beta(\boldsymbol{Q}_{t-1} - \overline{\boldsymbol{R}})$$

It is guaranteed to be positive definite as long as the initial parameters α and β are all positive and that $\alpha + \beta < 1$.

The integrated DCC model on the other hand assumes that the quasi-correlation matrix has a unit root process that is, the process has no tendency to revert to an unconditional value and is useful in modelling correlations that have structural breaks and are unlikely to be reversed. The specification of the quasi-correlation process under the integrated DCC model is given by:

$$\boldsymbol{Q}_t = \lambda \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} + (1 - \lambda)\boldsymbol{Q}_{t-1}$$

The dynamic parameters of both models are then estimated using maximum likelihood. Rescaling was also done in order to ensure that the quasi-correlation matrix is indeed a good approximation of the correlation matrix. This was done by both pre-multiplying and post-multiplying the square root of the diagonal elements of the quasi-correlation matrix with the quasi-correlation matrix. That is, the final estimated correlations are given by:

$$\boldsymbol{R}_t = \mathrm{diag}\{\boldsymbol{Q}_t\}^{-\frac{1}{2}}\boldsymbol{Q}_t\mathrm{diag}\{\boldsymbol{Q}_t\}^{-\frac{1}{2}}$$

In summary, the estimation of the parameters of the DCC models was done by utilizing a two-step estimator. Since the log-likelihood for multiple series can be expressed as the sum of the log-likelihood of the variance parameters and the log-likelihood of the correlation parameters, the first step of the estimation was done by maximizing the variance part of the likelihood function which is taken care of by the ARMA-GARCH estimation. The standardized residuals were then obtained from the first step and the log-likelihood of the correlation parameters was maximized by the estimation of the DCC specification.

Correlation Proxy

To evaluate the forecast performance of the correlation models, several rolling window correlations were computed as proxy for the true correlations. The number of observations used in the rolling windows was based on common maturity terms of derivative contracts involving correlations, which include 1-month, 3-month, 6-months, 1-year, and 2-year terms. The correlations used to settle these contracts, which are called realized correlations, are basically computed using the daily log returns of the assets for the entire term of the contract. Thus, the computed 22-day, 60-day, 125-day, 250-day, and 500-day rolling window correlations which are used as proxy for the true correlation can be also called the 1-month, 3-month, 6-month, 1-year, and 2-year realized correlations. It should be noted however that these rolling correlations do not necessarily reflect the true value of the actual correlation at a specific day since it can only be computed from intraday data and that the rolling correlations are computed from data spanning several months. The rolling correlations, however, are utilized to observe the general trends and patterns of the actual correlation levels across time in the sense that a good correlation model should efficiently capture the dynamic movements of these proxy correlations.

Results and Discussion

Descriptive Analysis

Figure 1a (in the Appendix) shows the levels of the Peso-Dollar exchange rate and the Philippine Stock Exchange index from the full sample of January 3, 2000 up to February 26, 2010. The composite index exhibits bullish periods between 2002 and 2007, and 2009 to 2010 and bearish periods on 2000 to 2002 and 2007 to 2009. For the earlier periods, the decline of the PSEi is subsequent to the effects of the tech bubble burst in the US. After 2002, a prolonged rebound can be seen as the PSEi rises until 2007 as the US housing bubble burst begins. The decline until 2008 shows its adverse effect to the local economy but 2009 shows signs of recovery as the PSEi levels begin to rise again. A strong evidence of a generally negative correlation is plausible as bullish stock market movements are generally accompanied by appreciative movements in the Peso with respect to the Dollar with the possible exception of the periods from early 2003 to 2004. Taking the viewpoint of Cappielo and De Santis' uncovered equity return parity condition, the co-movement of the Peso-Dollar exchange rate and PSE index from this period suggests that the Philippines had higher expected equity returns than that of the US during this time which might be coupled to a positive local economy outlook while the US is recovering from the 2000 crisis. Also, the last three quarters of 2007 show both series being positively correlated once again as they both drop steadily. This might be attributed to the adverse effect of the housing bubble burst in the US economy, which caused the depreciation of the Dollar, while the crisis affects the global equity markets.

Moreover, Figure 1b shows the time plot of the log returns for both assets by using the dlog[1] transformation. The returns of both assets appear to be stationary but volatility clustering and outliers are evident especially during the end of recessionary periods.

The sample correlation coefficients between the two daily log return series using moving windows of 22 days (i.e., 1 month), 60 days (i.e., 3 months), 125 days (i.e., 6 months), 250 days (i.e., 1 year), and 500 days (i.e., 2 years) are shown in Figure 2. The right and left axis of the graph show the short- (i.e., 1, 3, and 6 months) and medium-term (i.e., 1 and 2 years) moving correlations respectively. It is evident that the correlation changes over time and appears to be decreasing in the most recent periods as the economy recovers from the global financial crisis. The five correlation curves in Figure 2 look quite different from each other. The medium-term correlations are much smoother and easier to interpret over the short-term correlations. The monthly correlations have a great deal of volatility which looks like noise while the 3-month and 6-month correlations appear less fluctuating. However, the medium-term correlations do not

[1] $\text{dlog}(P_t) = \log(P_t) - \log(P_{t-1}) \approx (P_t - P_{t-1}) / P_{t-1}$, where P_t is the price of the asset at time t and log() is the natural logarithm function.

capture the actual movements since the over-all pattern is most evident. There are no statistical criteria in choosing between these measures thus, in comparing the results of the correlation forecasting models, all of these five measures will be used as points of comparison.

Figures 3a and 3b show the histogram and summary statistics of the prices and log returns respectively of the Peso-Dollar exchange rate and PSEi for both in- and out-of-sample periods. For the in-sample, the levels of the exchange rate and composite index are skewed to the left (Sk=-0.65) and right (Sk=0.89) respectively while the out-of-sample observations exhibit a more symmetric distribution (Sk=-0.24) for the exchange rate and a multi-modal distribution for the index. On the other hand, the distribution of the in-sample log returns for both series are generally asymmetric (Sk=-5.92 for exchange rate returns, Sk=0.58 for PSEi returns) and with excessive kurtosis (K=145.59 and K=19.71) which suggests non-constant conditional volatilities. The out-of-sample log returns for both series are more platykurtic (K=2.70 and K=4.11) and the Jarque-Bera test suggests that the out-of-sample returns for the Peso-Dollar exchange rate are normally distributed (test statistic=1.54, p=0.4623).

Univariate Analysis

The model building process for the mean-variance specification of the Peso-Dollar exchange rate and PSE index log returns will only consider the in-sample observations as the estimation sample. Tables 1a and 1b show the results of the Dickey-Fuller GLS (ERS) test for unit root for the log returns of the Peso-Dollar exchange rate and PSEi respectively. The test equations for the GLS detrended residuals of both log returns all have significant coefficients while the Elliott-Rothenberg-Stock DF-GLS test statistics (i.e., -9.34 and -36.82 for exchange rate and PSEi returns respectively) are both less than the critical values at 1% level of significance (i.e., -3.48). Thus, there is sufficient evidence to conclude that the log returns for both series are stationary[2]. This result would enable the de-GARCHING process of the DCC model estimation to allow for the modelling of the mean and variance processes with common models such as the ARMA and GARCH respectively.

The Univariate Box and Jenkins model building procedure was done to separately capture the mean and variance processes for each return series. Tables 2a and 2b show the final estimation output for the fitted models.

[2] "covariance or weakly stationary"

For the log returns of the Peso-Dollar exchange rate, an ARMA(1,3)-TGARCH(1,1) with conditional standardized Student-t (df=6.74) innovations was postulated after analyzing the sample partial autocorrelation function at different lag intervals of the log returns and squared log returns of the exchange rate while refining the equations by adding and dropping autoregressive (AR), moving average (MA), and volatility threshold terms until all the coefficients become significant at the 10% level. The joint estimation results are summarized in Table 2a. The model suggests that the log returns of the Peso-Dollar exchange rate are serially correlated because of the significant AR and MA terms and that its conditional volatility is not constant through time. Because the threshold term (-0.072) is significant, there is sufficient evidence that the effect of negative returns on future volatility is higher compared to positive returns, a phenomenon known as a leverage effect.

The same model building process was done for the log returns of the PSEi which is summarized in Table 2b. An AR(1)-TGARCH(1,1) with conditional standardized Student-t (df=5.12) innovations was jointly estimated as the final model. As with the log returns of the Peso-Dollar exchange rate, the log returns of the composite index exhibit dynamic persistence and serial correlations among returns while having time-varying volatilities with positive leverage effects (0.115).

After capturing the mean and the variance processes, the standardized residuals were obtained for both return series which would serve as the input series in the estimation of the correlation models.

In-Sample Performance

The results of the quasi-correlation model estimation for the mean-reverting dynamic conditional correlation model are summarized in Table 3a. For a model with correlation targeting, the intercept of the quasi-correlation specification is a function of the average cross-products of the standardized residuals which is labelled as the R matrix and whose coefficients are shown in the table. The estimated alpha of 0.000386 (z-statistic=0.031, p=0.9755) is not statistically significant while the estimated beta of 0.854088 (z-statistic=17.498, p=0.0000) is statistically significant. Judging form the estimated mean-reverting DCC model, there seems to be sufficient evidence to say that the dynamic conditional correlation is not dependent on previous shocks but only to its previous value.

The initial values of alpha (0.05) and beta (0.86) where chosen since these values maximized the log-likelihood function. To see whether the estimation results are robust in terms of the initial values used, several runs of the maximum likelihood estimation were done while varying the initial values of alpha and beta and imposing the condition that their sum should be less than 1 to ensure positive definiteness of the resulting correlation matrices. The contour plots of the log-likelihood and estimated coefficients are shown in Figure 4. From Figure 4a, it can be seen that the maximum likelihood was achieved for the lower alpha and higher beta values, specifically at 0.05 and 0.86 with a log-likelihood of -2299.238. Changing the initial values also has an effect on the estimated alpha and beta coefficients, as evident from Figures 4b and 4c.

For the integrated dynamic conditional correlation model, the quasi-correlation estimation results are summarized in Table 3b. Unlike the mean-reverting DCC, the integrated DCC has only one parameter to be estimated. The initial value of 0.01 for lambda of the maximum likelihood estimation was chosen in the same manner as that for the mean-reverting DCC. A plot of the initial values of lambda with the log-likelihood and the estimated lambda coefficients appears in Figure 5. The graph shows that the log-likelihood achieves its highest value (-2318.879) for the smallest initial value of lambda (0.01) while the absolute log-likelihood exponentially increases as the initial value increases. The estimated lambda coefficient of 0.005542 (z-statistic=3.224, p=0.0013) is significantly different from zero which indicates a substantial persistence of the correlations from the unconditional level.

It should be noted that although convergence was not achieved for both mean-reverting and integrated DCC, Engle and Sheppard (2001) used only one iteration for the maximum likelihood estimation of the parameters since there is no guarantee that increasing the number of iterations would increase the log-likelihood function.

The estimated in-sample correlations for both the mean-reverting and integrated DCC models were compared in Figure 6a. The graph showed that the forecasted correlations using the integrated DCC model had a start-up problem as the model produced wild estimates for the first two months of the in-sample. To give a better picture, Figure 6b showed the graph of the estimated correlations of both models from March, 2000 to December, 2008, taking away the wild forecasts of the integrated DCC model before this period. The exhibit showed that the forecasts from the integrated DCC model are more persistent than those from the mean-reverting

DCC model. However, the range of fluctuations were less pronounced in the mean-reverting model since the forecasted correlations for the period shown were as low as approximately -0.03 and as high as -0.022 while the forecasts of the integrated DCC model ranged from -0.022 to as high as 0.08. For both models, the long-run correlation between the log returns is generally negative which is consistent with literature as a high PSE index return and low exchange rate return is indicative of a healthy economy. However, there are some positive correlations forecasted in 2005 and 2008 from the integrated DCC model due to the co-movements of both Peso-Dollar exchange rate and PSEi in the months leading to these years.

For comparison purposes, several multivariate GARCH models such as the constant conditional correlation, diagonal VECH, and diagonal BEKK models were also estimated, the results of which are summarized in Table 4. As in the DCC models, the standardized residuals for both the log returns of the Peso-Dollar exchange rate and PSEi with zero mean specifications were used as the input series for the estimation of the multivariate GARCH models.

Figure 7a shows the correlation estimates from the multivariate GARCH models with those from the DCC models. Once again, the start-up problem of the integrated DCC model is distorting its overall pattern thus, Figure 7b shows the forecasted correlations once more using the truncated sample. The top part of the graph shows the forecasted correlations from the integrated DCC and diagonal VECH models which show fluctuations near the zero line, although the integrated DCC correlation forecasts are more persistent while the diagonal VECH forecasts are more volatile perhaps due to the non-positive definiteness of the forecasted correlation matrices inherent in the model itself. The bottom part of the graph shows the forecasts using the mean-reverting DCC, CCC, and diagonal BEKK models. The CCC fails to capture any dynamic pattern while being above the unconditional level of the diagonal BEKK and mean-reverting DCC estimates. The diagonal BEKK estimates are also volatile around the same level as the diagonal VECH estimates but have less extreme forecasts.

The forecasted correlations from all the models are then compared to the short-term realized correlations which are shown in Figure 8. It can be seen that the integrated DCC forecasts was the only model to capture the dynamic movements of the short-term correlations, especially for the 3-month and 6-month rolling window. The other models' forecasts on the other hand exhibit a much less dynamic pattern, not being able capture the shape of the correlation patterns from the realized correlations. To closely examine the trends of the forecasts, they were also compared to the medium-term realized correlations, as shown in Figure 9, since they have smoother shapes and have lesser fluctuations. From Figure 9b-1, the integrated DCC forecasts for the earlier months were problematic since they were very different but soon recovered, as shown in Figure 9b-2, as it closely follows the trend of the 1-year and 2-year realized correlations. As in Figure 8, the other models failed to capture the persistent pattern of the medium-term realized correlations.

To evaluate the performance of the models in estimating the correlations, forecast error measures such as the root mean squared error, mean absolute error, mean absolute percentage error, Theil inequality coefficient, and the bias, variance, and covariance proportions of the mean squared forecast error are computed for each model as compared to the different realized correlations, which is summarized in Table 5. In comparing forecasts of the same series across different models, the RMSE and MAE are used since these statistics depend on the scale of the dependent variable. From the table, it can be seen that the integrated DCC model yielded the lowest RMSE for the short-term realized correlations while the mean-reverting DCC model is the lowest for the medium-term realized correlations. However, the integrated DCC model yielded the lowest MAE for all the realized correlations. These results are also evident in the plot of the rolling window used in the computation of the realized correlation versus the different forecast error measures for each model, as shown in Figure 10. The integrated DCC model performed best in terms of RMSE for the short-term correlations but performed the worst for medium-term correlations. On the other hand, the integrated DCC model uniformly had the lowest MAE for all rolling window values. This might be attributed to the wild forecasts that the integrated DCC produced during the start-up months and that the RMSE exaggerates its effect since it is a squared error measure unlike the MAE which is an absolute error measure. Thus, it can be said that the integrated DCC model is the model of choice for capturing the patterns in the in-sample correlations between the log returns of the Peso-Dollar exchange rate and PSE index due to its appealing empirical forecast properties.

Out-of-Sample Performance

For the out-of-sample forecasting performance of the models, the observations from January 5, 2009 to February 26, 2010 were used and two types of forecasting were employed: rolling sample and dynamic forecasting.

Rolling Sample Forecasts

Figure 11 shows the 1-day, 2-day, 3-day, 4-day, and 5-day ahead correlation estimates from the DCC and multivariate GARCH models. There is not much difference with these graphs in terms of the forecast horizon since they are closely spaced with each other. Among the models, the integrated DCC model generated a different forecast pattern which is generally declining while the rest of the models still fluctuate around an unconditional level.

The 1-day ahead forecasted correlations from all the models are then compared to the short-term realized correlations which are shown in Figure 12. As in the in-sample results, the integrated DCC model is the only model that closely captured the trend of the declining realized short-term correlations though it doesn't capture its specific movements. The forecasts of other models were still relatively level and do not reflect the declining correlations. These 1-day ahead forecasts were also compared with the medium-term realized correlations in Figure 13. Once again, the integrated DCC model dominated the rest in following the downward trend of the correlations.

To evaluate the performance of the models in estimating the correlations, forecast error measures as in the in-sample analysis were also computed for each model as compared to the different realized correlations and forecast horizons, which is summarized in Table 6. It can be seen that for the 1-month and 2-month realized correlations, the integrated DCC has the lowest RMSE and MAE across all forecast horizons. On the other hand, the mean-reverting DCC has the lowest RMSE and MAE for the 2-year realized correlations. For the 6-month and 1-year realized correlations, the integrated DCC has the lowest RMSE while the mean-reverting DCC has the lowest MAE.

These results are also evident in the plot of the rolling window used in the computation of the realized correlation versus the different forecast error measures of the 1-day ahead forecasts for each model, as shown in Figure 14. In terms of the RMSE, the integrated DCC model was the lowest for up to a 300-day rolling window and then the mean-reverting DCC became the lowest thereafter. For the MAE, the integrated DCC model performed best just before the 100-day rolling window and the mean-reverting DCC model then performed best for rolling windows greater than 100 days.

At this point, the integrated DCC model seem to perform well in capturing the patterns of short-term realized correlations while it's the mean-reverting DCC model for the medium-term realized correlations. To formally test the predictive accuracy of the DCC model, say the integrated DCC model, several Diebold-Mariano tests using the squared error loss function were done to test whether the integrated DCC model significantly outperforms the other models in forecasting the realized correlations across the different rolling windows and forecast horizons. The results are summarized in Table 7. The Diebold-Mariano test statistics are approximately normally distributed with mean zero and variance one such that a left-tailed test would reject the null hypothesis of equal predictive accuracy if the test statistic is less than -2.32 at the 1% level of significance in favour of the alternative hypothesis that the integrated DCC model has a better predictive accuracy than the other models. The Diebold-Mariano tests results show that there is sufficient evidence to conclude that the integrated DCC model has a significantly greater predictive accuracy in forecasting the 3-month realized correlation across all forecast horizons and other models at 10% level of significance since the test statistics are all less than 1.645. However, the same conclusions cannot be said for the other realized correlations as proxies. In the case of the mean-reverting DCC model, if the alternative hypothesis is reversed such that a right-tailed test rejects the null hypothesis at the 10% level of significance for test statistics greater than 1.645. The table shows that the mean-reverting DCC has the same predictive accuracy across all forecast horizons than the integrated DCC since all the Diebold-Mariano test statistics are all less than 1.645 if the 2-year realized correlations are used as proxy.

Based on the results of the forecast error measures and the Diebold-Mariano tests, there is sufficient evidence to conclude that the integrated DCC model is the most optimal model among the five correlation models in terms of short-run forecasts of the patterns of short-term realized correlations specifically the 3-month realized correlations of the log returns of the Peso-Dollar exchange rate and PSE index. This may be attributed to the fact that short-term correlations are generally volatile and persistent and the integrated DCC model performs well for persistent correlation series. However, for medium-term realized correlations of the log returns of the series, the mean-reverting DCC model seem to perform the best since these realized correlations are generally smoother and fluctuate around a fixed mean, and the mean-reverting DCC model performs well for correlations which revert to a constant value though these finding though these results are not statistically significant according to the Diebold-Mariano test but are only based on empirical forecast error measures.

Dynamic Forecasts

For the long-run forecasts of correlations, Figure 15 shows the dynamic out-of-sample forecasts of the five models which are estimated using only the data from the in-sample. Since the coefficients of the integrated DCC model add up to 1, the best forecast of the correlation for all horizons is the forecasted correlation 1-day ahead of the in-sample. Thus, the dynamic forecasted correlations for the integrated DCC model are constant at the onset. But unlike the dynamic forecast of the CCC which is also constant, the integrated DCC forecast is pegged at the 1-day ahead forecast while the CCC forecast reflects the estimated long-run constant correlation. This is especially true for the other mean-reverting models such as the mean-reverting DCC, diagonal VECH, and diagonal BEKK since their dynamic forecasts for further horizons will eventually be constant at the estimated unconditional mean correlation. It can also be seen that for the mean-reverting DCC, diagonal VECH, and diagonal BEKK, the dynamic forecasts continue to change for as long as 5 days ahead before settling at a fixed value.

The forecasted correlations using dynamic forecasting are also compared with the short- and medium-term realized correlations in Figures 16 and 17. Because of the declining pattern of the realized correlations in the out-of-sample, all the models overestimated the correlation patterns but the mean-reverting DCC dynamic forecasts were the one closest to the average level of the realized forecasts.

Table 8 shows the forecast error measures as also computed in the in-sample and rolling sample forecast analysis in each model as compared to the different realized correlations to evaluate the performance of the models in estimating the correlations. The statistics indicate that the mean-reverting DCC model has the lowest RMSE and MAE across all realized correlations in terms of its dynamic correlation forecasts.

These results are also evident in the plot of the rolling window used in the computation of the realized correlation versus the different forecast error measures of the dynamic forecasts for each model, as shown in Figure 18. Because the 1-day ahead forecast of the integrated DCC model is positive while the realized correlations for the out-of-sample periods were declining, it yielded the highest error statistics across all rolling window. However, the mean-reverting DCC performed well across all rolling windows, uniformly yielding the lowest RMSE and MAE.

Based on the results of the forecast error measures, there is evidence to say that the mean-reverting DCC model is the optimal model in dynamically forecasting the out-of-sample correlation level for the log returns of the Peso-Dollar exchange rate and PSE index.

Conclusions

An understanding in the nature and scope of correlations between the Peso-Dollar exchange rate and PSEi returns is important in the estimation of risks for optimal hedging since it only does not involve only the quantification of individual volatilities but also include their pairwise correlations; as well as perceiving some ways to respond to the challenges in the economy. The dynamic conditional correlation model was used to estimate the correlation between these two returns. By employing both the mean-reverting and integrated DCC model, the results in this paper show that the correlation between the two returns is generally negative and is not really constant, but actually time-varying which is in accordance to the results of economic theories. The DCC models also produced more preferable results as to its flexibility, simplicity, and coherence with literature against other correlation models. Fluctuations in the correlations were caused by news affecting both the foreign exchange and equity markets. The integrated DCC model showed optimal forecast performance for the in-sample correlation patterns and rolling-sample forecasts of 1-day to 5-day horizons in terms of short-term realized correlations. On the other hand, the mean-reverting DCC model had the most desirable forecast properties for dynamic long-run forecasts and 1-day to 5-day rolling sample forecasts in terms of medium-term realized correlations. In terms of the short-run forecasting performance, the integrated DCC model was significantly higher in predictive accuracy than the other models using only the 3-month realized correlations as proxy.

Directions for Further Research

Other variations and improvement have been postulated for the original DCC model. With the advent of these variations, it is recommended to explore these variations of the DCC model to create a possibly better correlation model for the two returns. It should also be noted that there could be some other variables, which are correlated with these two that might improve the correlation model. A creation of such model would be beneficial in developing an extensive model for the estimation of risks for optimal hedging. Also, with high frequency data becomingly readily available, further forecast evaluation of the DCC models in this paper should be extended to include daily realized correlations as the basis of comparison and see whether the model can efficiently forecast them.

Acknowledgments

The researchers would like to express their deepest gratitude to Mr. Gregorio A. Vargas of Singapore Management University School of Economics for sharing his EViews program codes for the estimation of the DCC models. Also, the researchers are grateful for Prof. Peter Cayton of the University of the Philippines School of Statistics and Ms. Lorelie Santos of Metrobank for their invaluable comments and suggestions regarding the study.

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Abridged Appendix: Figures and Tables

Figure 1a. Time Plot of the Closing Daily Prices of the Philippine Stock Exchange Index and Peso-Dollar Exchange Rate from January, 2000 to February, 2010

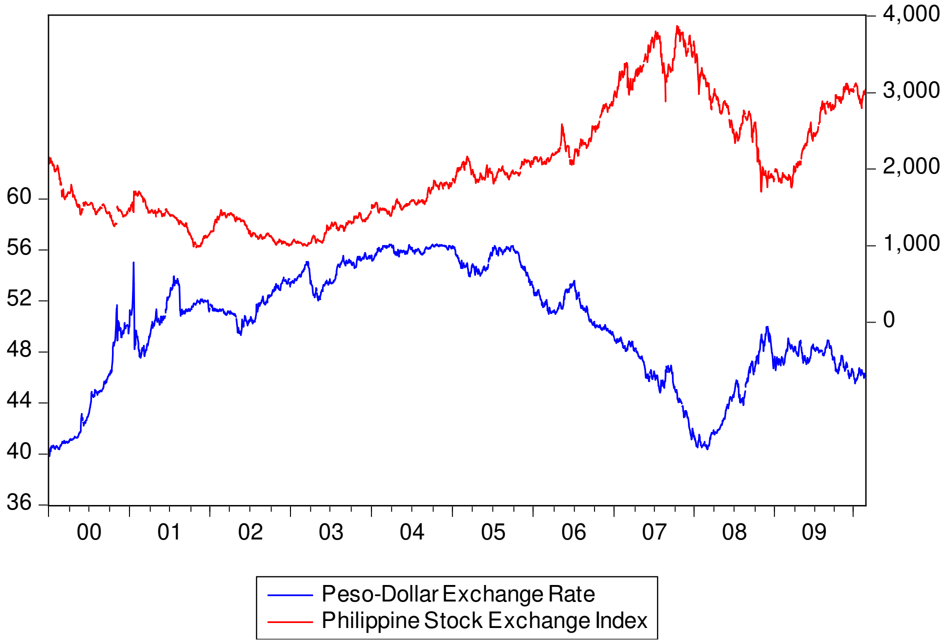


Figure 1b. Time Plot of the Log Returns of the Peso-Dollar Exchange Rate and Philippine Stock Exchange Index from January, 2000 to February, 2010

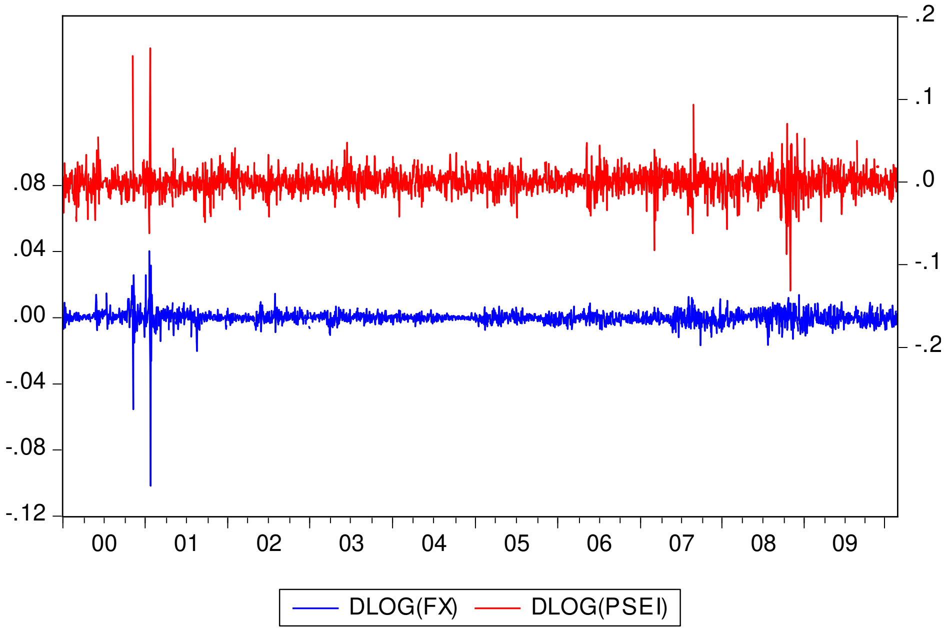


Figure 2. Time Plot of the 22-Day (1-Month), 60-Day (3-Month), 125-Day (6-Month), 250-Day (1-Year), and 500-Day (2-Year) Realized Correlations between the Log Returns of the Peso-Dollar Exchange Rate and Philippine Stock Exchange Index from January, 2000 to February, 2010

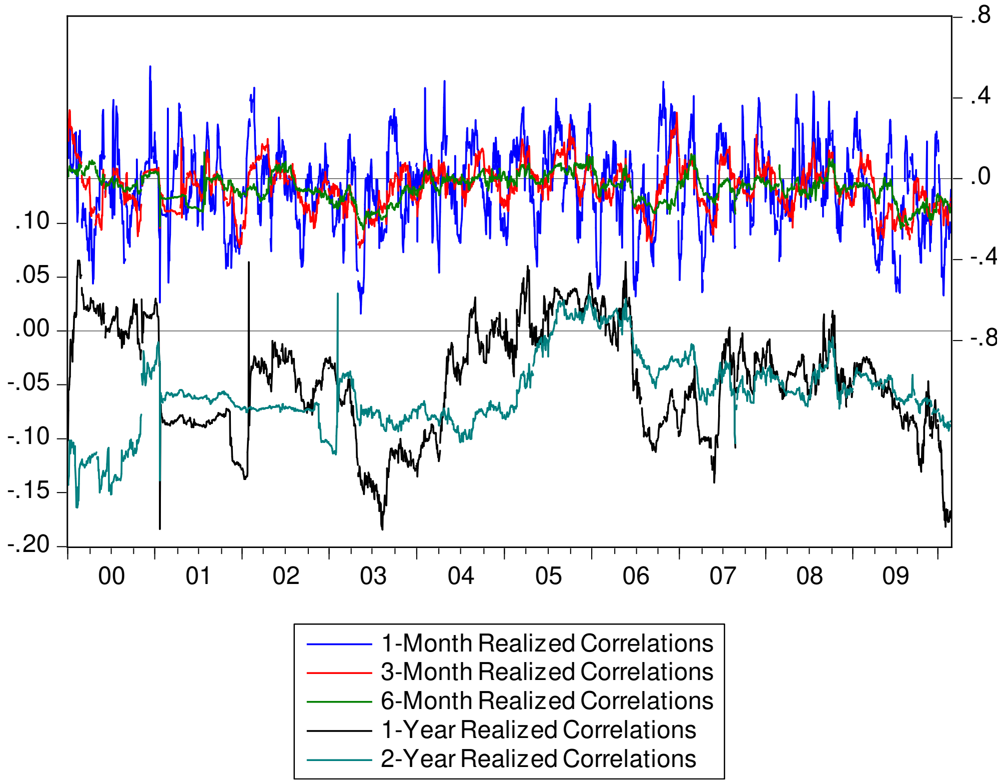


Table 3a. Estimated Parameters of the Mean-Reverting DCC Model between the Log Returns of Peso-Dollar Exchange Rate and the Log Returns of Philippine Stock Exchange Index with an ARMA-TGARCH Specification

LogL: MR_DCC
Method: Maximum Likelihood (BHHH)
Sample: 1/04/2000 12/24/2008
Included observations: 2212
Evaluation order: By observation
Estimation settings: tol= 1.0e-05, derivs=accurate numeric
Initial Values: ALPHA(1)=0.05000, BETA(1)=0.86000
Convergence not achieved after 1 iteration
Q = (1 - ALPHA(1) - BETA(1))*R + ALPHA(1)*RESID(-1)*RESID(-1)' + BETA(1)*Q(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
R(1,1)	1.012139	--	--	--
R(1,2)	-0.026112	--	--	--
R(2,2)	1.066428	--	--	--
ALPHA(1)	0.000386	0.012565	0.030715	0.9755
BETA(1)	0.854088	0.048812	17.49752	0.0000

Log likelihood	-2299.238	Akaike info criterion	2.080686
Avg. log likelihood	-1.039439	Schwarz criterion	2.085841
Number of Coefs.	2	Hannan-Quinn criter.	2.082569
Minimum Eigenvalue	0.145845		

Table 3b. Estimated Parameters of the Integrated DCC Model between the Log Returns of the Peso-Dollar Exchange Rate and the Log Returns of Philippine Stock Exchange Index with an ARMA-TGARCH Specification

LogL: I_DCC
Method: Maximum Likelihood (BHHH)
Sample: 1/04/2000 12/24/2008
Included observations: 2212
Evaluation order: By observation
Estimation settings: tol= 1.0e-05, derivs=accurate numeric
Initial Values: LAMBDA(1)=0.01000
Convergence not achieved after 1 iteration
Q = LAMBDA(1)*RESID(-1)*RESID(-1)' + (1-LAMBDA(1))*Q(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
LAMBDA(1)	0.005542	0.001719	3.224459	0.0013

Log likelihood	-2318.879	Akaike info criterion	2.097539
Avg. log likelihood	-1.048318	Schwarz criterion	2.100117
Number of Coefs.	1	Hannan-Quinn criter.	2.098481
Minimum Eigenvalue	0.000409		

Figure 6a. Time Plot of the Forecasted In-Sample Correlations between the Log Returns of the Peso-Dollar Exchange Rate and Philippine Stock Exchange Index from January, 2000 to December, 2008 using the Mean-Reverting and Integrated DCC Models

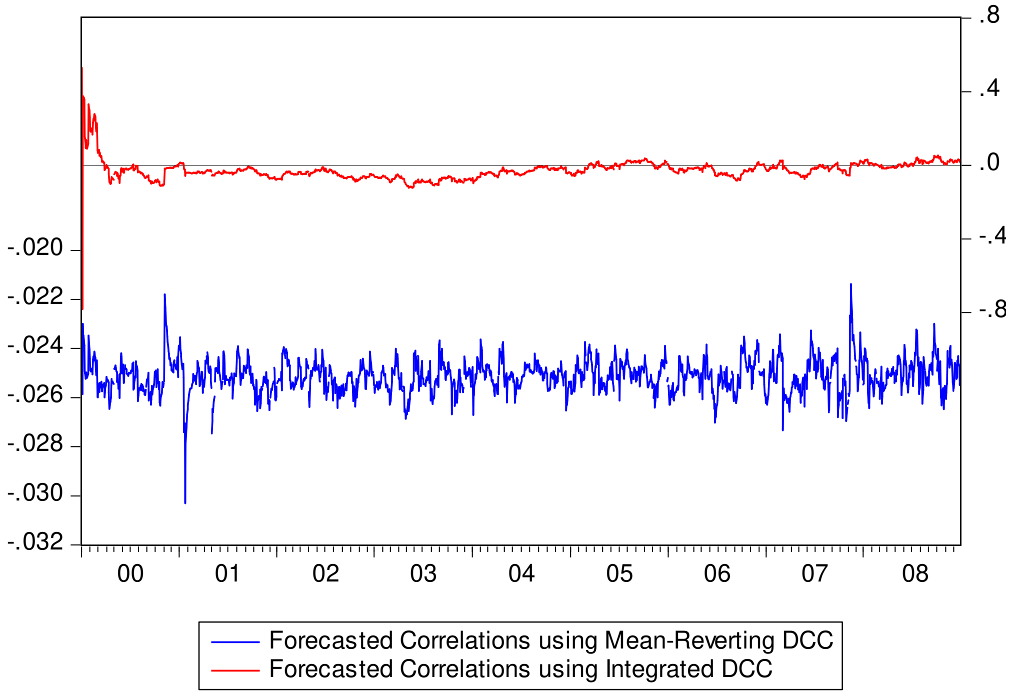


Figure 6b. Time Plot of the Forecasted In-Sample Correlations between the Log Returns of the Peso-Dollar Exchange Rate and Philippine Stock Exchange Index from March, 2000 to December, 2008 using the Mean-Reverting and Integrated DCC Models

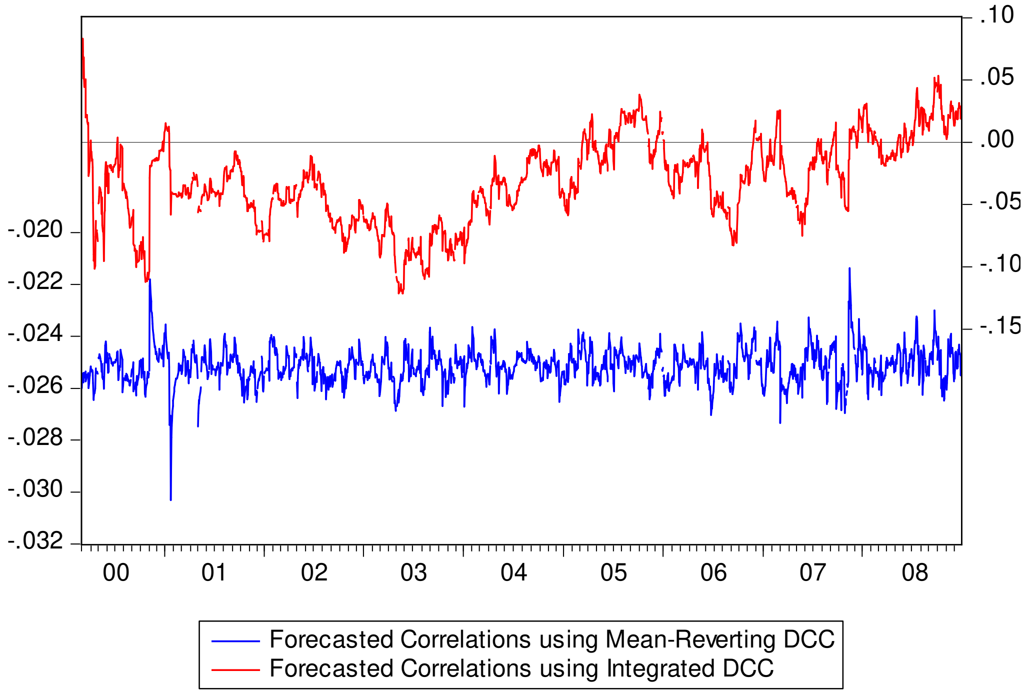
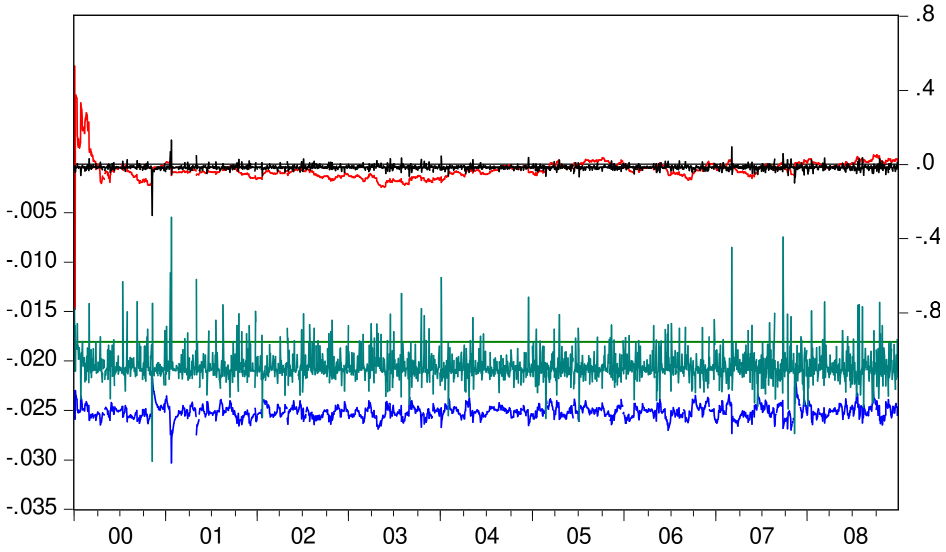


Figure 7. Time Plots of the Forecasted In-Sample Correlations between the Log Returns of the Peso-Dollar Exchange Rate and the Philippine Stock Exchange Index using the Mean-Reverting and Integrated Dynamic ConditionalCorrelation Models, Constant Conditional Correlation Model,Diagonal VECH Model, and Diagonal BEKK Model

a. January, 2000 to December, 2008



b. March, 2000 to December, 2008

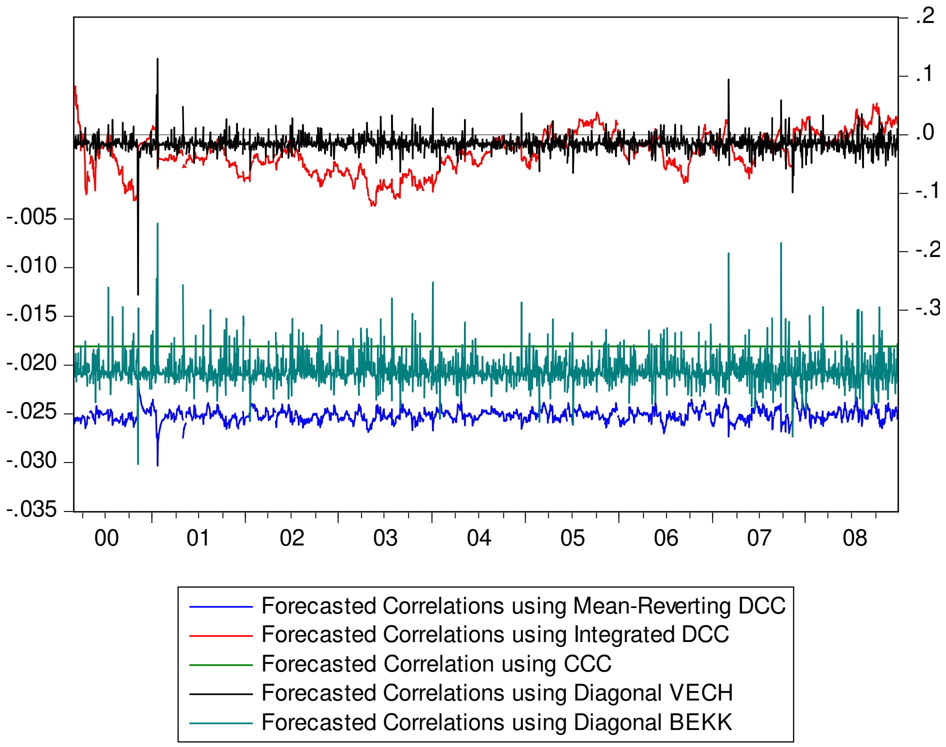


Table 5. In-sample Forecasting Performance of the Mean-Reverting DCC, Integrated DCC, CCC, Diagonal VECH, and Diagonal BEKK Models as Compared to the 22-Day, 60-Day, 125-Day, 250-Day, and 500-Day Realized Correlations

Date: 04/01/11 Time: 10:57
Forecast Sample: 1/04/2000 12/24/2008
Method: Static
Included Observations: 2212

Correlation Proxy	Forecast Error Measures	MR-DCC	I-DCC	CCC	VECH	BEKK
	RMSE	0.199287	0.189891	0.199941	0.202620	0.200031
	MAE	0.160148	0.152011	0.160524	0.162692	0.160644
	MAPE	128.5443	141.5271	118.1553	117.3225	121.3061
22-Day	THEIL	0.878250	0.729461	0.909462	0.913355	0.899608
	Biasprop	0.000457	0.000159	0.003205	0.004913	0.001965
	Varianceprop	0.996770	0.604763	0.996795	0.847256	0.980894
	Covarianceprop	0.002773	0.395077	2.30E-17	0.147831	0.017141
	RMSE	0.108278	0.092251	0.109325	0.111858	0.109122
	MAE	0.084624	0.071189	0.085203	0.087438	0.085197
	MAPE	218.0804	217.3490	180.4302	178.3159	195.5056
60-Day	THEIL	0.782000	0.536762	0.832032	0.838574	0.814929
	Biasprop	0.006200	0.005218	0.020325	0.027261	0.014485
	Varianceprop	0.986642	0.371916	0.979675	0.722696	0.956086
	Covarianceprop	0.007158	0.622866	4.25E-17	0.250043	0.029429
	RMSE	0.066365	0.061570	0.068138	0.070958	0.067564
	MAE	0.052208	0.044822	0.053464	0.055743	0.053085
	MAPE	1065.105	626.7145	778.9090	534.5831	858.9989
125-Day	THEIL	0.661295	0.460301	0.730397	0.744698	0.705284
	Biasprop	0.032560	0.026979	0.078042	0.095411	0.060236
	Varianceprop	0.952476	0.047905	0.921958	0.543435	0.894914
	Covarianceprop	0.014964	0.925116	6.68E-17	0.361154	0.044850
	RMSE	0.053166	0.054897	0.055938	0.059282	0.054985
	MAE	0.043066	0.038932	0.045066	0.047470	0.044400
	MAPE	301.6361	359.9563	237.5051	213.0582	259.5079
250-Day	THEIL	0.584788	0.441584	0.667137	0.690588	0.636730
	Biasprop	0.102570	0.076313	0.185422	0.206975	0.154811
	Varianceprop	0.878447	0.000710	0.814578	0.397373	0.793387
	Covarianceprop	0.018983	0.922977	7.61E-17	0.395652	0.051803
	RMSE	0.048983	0.066374	0.053985	0.057957	0.052282
	MAE	0.041791	0.040528	0.046760	0.049736	0.045054
	MAPE	100.0106	92.47362	97.30522	100.0270	98.35501
500-Day	THEIL	0.523890	0.523039	0.624615	0.655434	0.587845
	Biasprop	0.441525	0.213732	0.538272	0.537489	0.505043
	Varianceprop	0.540991	0.052896	0.461728	0.165353	0.452626
	Covarianceprop	0.017484	0.733373	5.87E-17	0.297158	0.042331

Figure 11. Time Plots of the Forecasted 1-Day, 2-Day, 3-Day, 4-Day, and 5-Day Rolling-Sample Correlations between the Log Returns of the Peso-Dollar Exchange Rate and the Philippine Stock Exchange Index from January, 2009 to February, 2010 using the Mean-Reverting and Integrated Dynamic Conditional Correlation Models, Constant Conditional Correlation Model, Diagonal VECH Model, and Diagonal BEKK Model

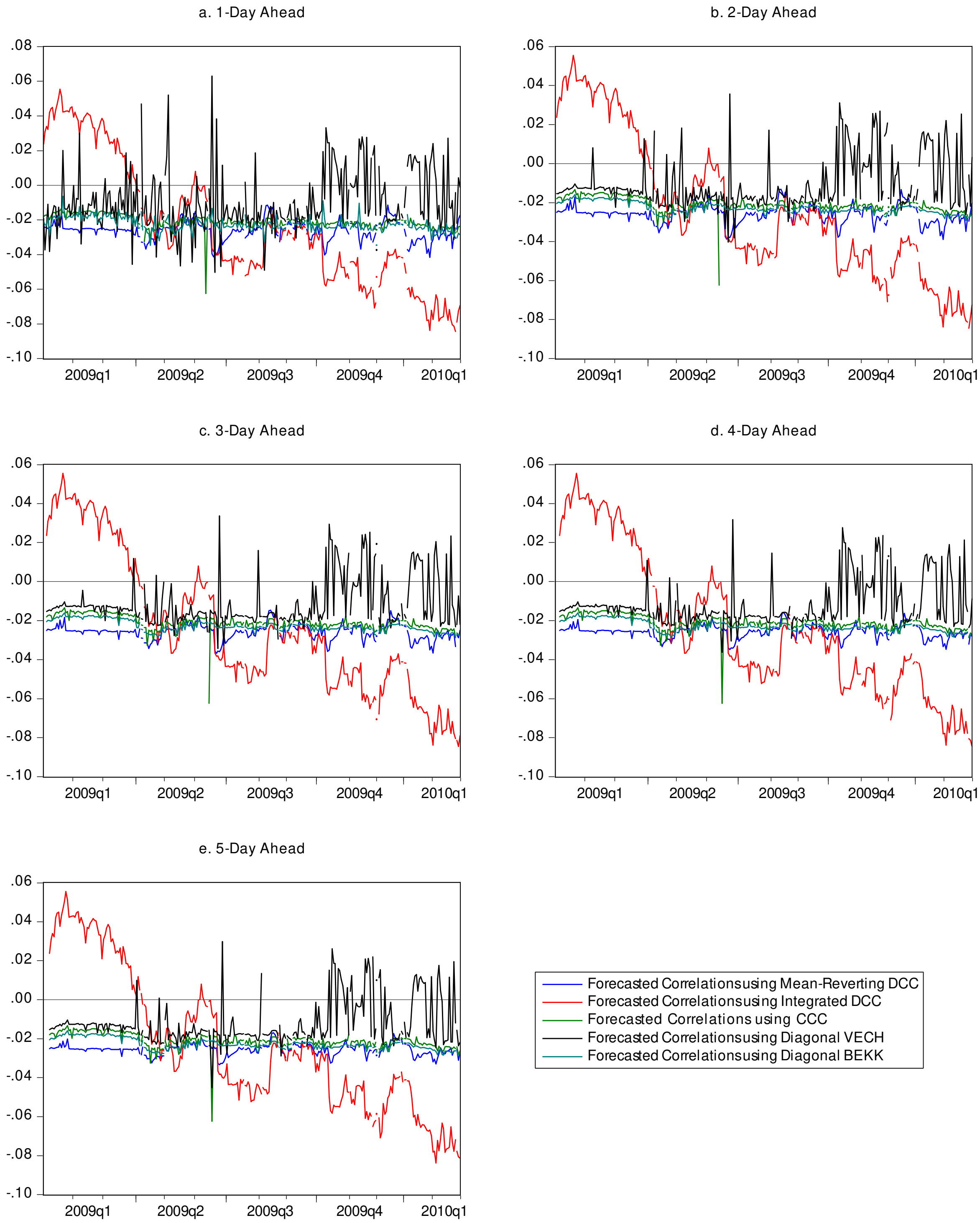


Table 6. Rolling-sample Forecasting Performance of the Mean-Reverting and Integrated DCC, CCC, Diagonal VECH, and Diagonal BEKK Models as Compared to the 22-Day, 60-Day, 125-Day, 250-Day, and 500-Day Realized Correlations for 1-Day to5-Day Forecast Horizons

Forecast Sample: 1/05/2009 2/26/2010 Included Observations: 278

Forecast Horizon (in Days)		1					2					3				
Correlation Proxy	Forecast Error Measures	MR-DCC	I-DCC	CCC	VECH	BEKK	MR-DCC	I-DCC	CCC	VECH	BEKK	MR-DCC	I-DCC	CCC	VECH	BEKK
22-Day	RMSE	0.241941	0.232292	0.245808	0.256303	0.245474	0.242735	0.233577	0.246196	0.254139	0.245283	0.243387	0.234807	0.246559	0.254403	0.245652
	MAE	0.202657	0.193020	0.205408	0.214632	0.205107	0.203195	0.193993	0.205775	0.213053	0.205006	0.203503	0.194875	0.206002	0.213212	0.205212
	MAPE	161.8774	165.7491	147.8250	159.7802	156.6112	160.3766	168.7406	146.4094	136.1068	151.9125	157.6576	167.2008	146.5911	141.6307	151.1157
	THEIL	0.853004	0.773961	0.883098	0.925805	0.877067	0.855608	0.777550	0.883280	0.926465	0.874911	0.857767	0.781200	0.883617	0.927546	0.875315
	Biasprop	0.183066	0.205946	0.195360	0.218773	0.190232	0.185456	0.207564	0.197788	0.222227	0.192619	0.188601	0.209976	0.200880	0.223552	0.195715
	Varianceprop	0.800048	0.641580	0.784536	0.636475	0.787514	0.800420	0.634547	0.781767	0.673627	0.796615	0.799317	0.626748	0.777806	0.676633	0.792659
	Covarianceprop	0.016886	0.152473	0.020103	0.144752	0.022254	0.014125	0.157889	0.020445	0.104146	0.010766	0.012082	0.163276	0.021314	0.099815	0.011626
60-Day	RMSE	0.143432	0.133992	0.145948	0.156080	0.145004	0.143823	0.134305	0.146142	0.154794	0.144955	0.144173	0.134595	0.146340	0.154554	0.145135
	MAE	0.126277	0.111458	0.127833	0.137437	0.127061	0.126624	0.111672	0.127991	0.136849	0.127105	0.126855	0.111811	0.128111	0.136488	0.127225
	MAPE	131.0800	119.4111	119.8817	118.1874	122.7331	130.4796	122.4627	118.5592	115.1127	122.4144	130.3378	120.1379	119.1092	117.9500	123.0382
	THEIL	0.756281	0.649966	0.791617	0.853540	0.780010	0.758931	0.651303	0.791938	0.859401	0.778657	0.761268	0.652700	0.792423	0.859033	0.779103
	Biasprop	0.475999	0.566565	0.508614	0.545905	0.499722	0.475941	0.566702	0.508179	0.547068	0.498447	0.475498	0.566605	0.507243	0.544094	0.497739
	Varianceprop	0.476470	0.262597	0.472501	0.311253	0.479786	0.483272	0.263035	0.472887	0.348651	0.492625	0.489138	0.263752	0.473342	0.358195	0.493345
	Covarianceprop	0.047531	0.170838	0.018885	0.142842	0.020492	0.040786	0.170262	0.018934	0.104281	0.008928	0.035364	0.169643	0.019416	0.097711	0.008916
125-Day	RMSE	0.107625	0.100616	0.110990	0.122601	0.109723	0.107972	0.101057	0.111187	0.121495	0.109601	0.108308	0.101481	0.111428	0.121243	0.109847
	MAE	0.086470	0.087717	0.091452	0.103054	0.089872	0.086942	0.088301	0.091626	0.101558	0.089710	0.087376	0.088855	0.091901	0.101283	0.090003
	MAPE	82.29827	111.3480	88.16849	103.9930	88.53436	82.92717	113.3726	88.47571	93.83133	86.31420	82.62617	114.8388	88.67836	93.73973	86.10061
	THEIL	0.690107	0.583440	0.736659	0.821932	0.720911	0.692832	0.585685	0.736963	0.829581	0.718720	0.695212	0.587895	0.737549	0.828612	0.719412
	Biasprop	0.623492	0.745627	0.659152	0.683311	0.651005	0.626038	0.746503	0.660877	0.686992	0.652725	0.628520	0.747912	0.662173	0.686436	0.654134
	Varianceprop	0.317003	0.090408	0.311164	0.157573	0.319593	0.322965	0.089656	0.309689	0.188714	0.331646	0.327539	0.089011	0.307945	0.195822	0.329910
	Covarianceprop	0.059506	0.163964	0.029684	0.159116	0.029401	0.050998	0.163841	0.029434	0.124295	0.015628	0.043941	0.163077	0.029882	0.117742	0.015956
250-Day	RMSE	0.063060	0.056732	0.066713	0.080867	0.065511	0.063352	0.056998	0.066839	0.079205	0.065269	0.063620	0.057254	0.066957	0.078551	0.065400
	MAE	0.050085	0.052115	0.055212	0.066559	0.053605	0.050368	0.052345	0.055314	0.065614	0.053461	0.050647	0.052625	0.055458	0.065199	0.053589
	MAPE	56.20191	88.00685	66.25184	81.21100	63.25070	56.39239	88.24478	66.27166	79.66764	62.99899	56.64975	88.57596	66.36438	79.02332	63.06377
	THEIL	0.560886	0.440029	0.622662	0.765516	0.602814	0.564581	0.442145	0.623257	0.770305	0.599548	0.567774	0.444242	0.623782	0.765730	0.600265
	Biasprop	0.630146	0.838762	0.684297	0.674639	0.669561	0.631485	0.839567	0.684584	0.686270	0.670911	0.632875	0.841137	0.685081	0.688932	0.671434
	Varianceprop	0.288327	0.003845	0.278034	0.073553	0.290246	0.299819	0.003961	0.277410	0.108648	0.311811	0.309293	0.004116	0.276856	0.118575	0.311311
	Covarianceprop	0.081527	0.157393	0.037668	0.251808	0.040193	0.068696	0.156472	0.038007	0.205082	0.017278	0.057832	0.154747	0.038064	0.192493	0.017255
500-Day	RMSE	0.036186	0.042599	0.040573	0.055534	0.039091	0.036348	0.042766	0.040626	0.053509	0.038751	0.036533	0.042947	0.040693	0.052776	0.038823
	MAE	0.033284	0.035233	0.038547	0.049660	0.036831	0.033502	0.035409	0.038590	0.048773	0.036620	0.033704	0.035618	0.038645	0.048290	0.036681
	MAPE	53.83185	71.07040	63.63397	80.93599	60.46368	54.09189	71.28290	63.64818	79.50885	60.10474	54.32832	71.54154	63.68312	78.67101	60.14862
	THEIL	0.411926	0.408245	0.491441	0.685142	0.464861	0.415125	0.410172	0.491900	0.684499	0.460153	0.418307	0.412312	0.492511	0.677786	0.460904
	Biasprop	0.846015	0.682154	0.896325	0.799220	0.887705	0.849494	0.684605	0.896214	0.830812	0.893020	0.851135	0.687163	0.895691	0.837241	0.892667
	Varianceprop	0.061489	0.251654	0.064315	0.002833	0.070862	0.072425	0.248520	0.064239	0.000503	0.088675	0.081895	0.244924	0.064114	0.001616	0.088701
	Covarianceprop	0.092497	0.066191	0.039360	0.197948	0.041434	0.078081	0.066875	0.039546	0.168684	0.018305	0.066970	0.067913	0.040195	0.161143	0.018632

Date: 04/02/11 Time: 09:37 Method: Rolling Sample

Forecast Sample: 1/05/2009 2/26/2010 Included Observations: 278

Forecast Horizon (in Days)		4					5				
Correlation Proxy	Forecast Error Measures	MR-DCC	I-DCC	CCC	VECH	BEKK	MR-DCC	I-DCC	CCC	VECH	BEKK
	RMSE	0.243950	0.236036	0.246711	0.254366	0.245986	0.244263	0.237160	0.246743	0.253975	0.246089
	MAE	0.203839	0.195815	0.205911	0.213144	0.205420	0.203924	0.196594	0.205901	0.212601	0.205364
	MAPE	155.2765	163.6263	145.1657	138.3737	150.9919	157.2370	168.1606	146.8039	140.7099	152.4457
22-Day	THEIL	0.859475	0.784946	0.883225	0.926630	0.875557	0.860803	0.788964	0.883043	0.924781	0.875607
	Biasprop	0.191871	0.212484	0.204387	0.225988	0.198872	0.196556	0.216392	0.209202	0.230269	0.203493
	Varianceprop	0.797959	0.619311	0.775276	0.678409	0.788890	0.794592	0.610049	0.770583	0.678519	0.783667
	Covarianceprop	0.010170	0.168204	0.020337	0.095603	0.012238	0.008852	0.173559	0.020216	0.091212	0.012840
	RMSE	0.144437	0.134762	0.146367	0.154182	0.145268	0.144737	0.135148	0.146529	0.154007	0.145454
	MAE	0.127072	0.111911	0.128189	0.136264	0.127301	0.127316	0.112059	0.128322	0.135936	0.127428
	MAPE	131.7613	124.4044	119.7189	113.3160	123.3792	131.5127	124.6426	119.3554	111.2964	123.2532
60-Day	THEIL	0.763147	0.653766	0.792213	0.856877	0.779432	0.764867	0.655846	0.792507	0.855103	0.779833
	Biasprop	0.475024	0.567215	0.507076	0.542979	0.496783	0.474875	0.567039	0.506700	0.541427	0.496184
	Varianceprop	0.494504	0.265236	0.475032	0.365098	0.494328	0.498758	0.266109	0.475858	0.370067	0.494958
	Covarianceprop	0.030471	0.167549	0.017891	0.091923	0.008889	0.026367	0.166853	0.017442	0.088506	0.008857
	RMSE	0.108616	0.101876	0.111610	0.121130	0.110076	0.108913	0.102339	0.111825	0.121031	0.110300
	MAE	0.087783	0.089362	0.092033	0.101175	0.090288	0.088228	0.089931	0.092345	0.101093	0.090604
	MAPE	82.55399	115.4881	87.72646	94.48875	86.01520	82.39083	116.5598	87.13774	93.16015	86.05260
125-Day	THEIL	0.697250	0.590086	0.737818	0.827119	0.719972	0.699014	0.592773	0.738260	0.825132	0.720459
	Biasprop	0.631071	0.750056	0.664233	0.686301	0.655553	0.634104	0.752187	0.666479	0.686887	0.657617
	Varianceprop	0.331137	0.088676	0.306729	0.199440	0.328276	0.333419	0.088174	0.304937	0.201717	0.326267
	Covarianceprop	0.037791	0.161267	0.029038	0.114259	0.016171	0.032477	0.159640	0.028584	0.111395	0.016117
	RMSE	0.063916	0.057589	0.067071	0.078264	0.065525	0.064218	0.058018	0.067229	0.077971	0.065670
	MAE	0.050905	0.052859	0.055548	0.064933	0.053710	0.051194	0.053194	0.055726	0.064743	0.053881
	MAPE	56.82882	88.74503	66.39026	78.41270	63.11558	57.06699	88.93599	66.51929	78.04170	63.24106
250-Day	THEIL	0.571014	0.447117	0.624347	0.762782	0.600894	0.574035	0.450776	0.625193	0.758892	0.601599
	Biasprop	0.633445	0.841089	0.685909	0.688348	0.671890	0.634732	0.840552	0.687083	0.689489	0.673186
	Varianceprop	0.316558	0.004344	0.276555	0.123945	0.310756	0.321462	0.004541	0.275264	0.127854	0.309335
	Covarianceprop	0.049997	0.154566	0.037536	0.187706	0.017354	0.043806	0.154907	0.037653	0.182657	0.017479
	RMSE	0.036726	0.043134	0.040732	0.052362	0.038881	0.036926	0.043350	0.040811	0.051963	0.038955
	MAE	0.033891	0.035847	0.038651	0.047954	0.036731	0.034081	0.036110	0.038711	0.047662	0.036800
	MAPE	54.54448	71.83720	63.63067	78.02135	60.18444	54.76577	72.12781	63.66107	77.54149	60.23727
500-Day	THEIL	0.421440	0.414697	0.492906	0.672909	0.461467	0.424427	0.417490	0.493705	0.667290	0.462159
	Biasprop	0.851561	0.690278	0.896602	0.838727	0.892433	0.851879	0.693864	0.896672	0.841299	0.892407
	Varianceprop	0.089972	0.240417	0.064276	0.002482	0.088732	0.096607	0.235193	0.064179	0.003215	0.088539
	Covarianceprop	0.058467	0.069305	0.039122	0.158791	0.018835	0.051514	0.070943	0.039149	0.155486	0.019054

Table 7. Diebold-Mariano Tests of Predictive Accuracy using the Squared Error Loss of the Integrated Dynamic Conditional Correlation Models versus the Mean-Reverting Dynamic Conditional Correlation Model, Constant Conditional Correlation Model, Diagonal VECH Model, and Diagonal BEKK Model using the 22-Day, 60-Day, 125-Day, 250-Day, ad 500-Day Realized Correlations as Proxy for the True Correlation

Null Hypothesis: Integrated DCC has equal predictive accuracy as the other model
Alternative Hypothesis: Integrated DCC has greater predictive accuracy than the other model
Date: 04/06/11 Time: 07:49
Forecast Sample: 1/05/2009 2/26/2010
Method: Rolling Sample
Included Observations: 2213

Correlation Proxy	Forecast Horizon	MR-DCC	CCC	VECH	BEKK
22-Day	1-Day	-1.68*	-2.35***	-3.30***	-2.32***
	2-Day	-1.58	-2.19**	-2.83***	-2.05**
	3-Day	-1.46	-2.04**	-2.72***	-1.90*
	4-Day	-1.34	-1.85*	-2.56***	-1.74*
	5-Day	-1.20	-1.66*	-2.35***	-1.56
60-Day	1-Day	-2.25**	-2.90***	-4.12***	-2.67***
	2-Day	-2.28**	-2.91***	-3.95***	-2.63***
	3-Day	-2.30**	-2.92***	-3.89***	-2.63***
	4-Day	-2.33***	-2.89***	-3.87***	-2.64***
	5-Day	-2.29**	-2.83***	-3.74***	-2.59***
125-Day	1-Day	-1.44	-2.06**	-3.17***	-1.86*
	2-Day	-1.41	-1.99**	-2.89***	-1.73*
	3-Day	-1.38	-1.94*	-2.80***	-1.68*
	4-Day	-1.35	-1.89*	-2.73***	-1.64
	5-Day	-1.30	-1.83*	-2.66***	-1.58
250-Day	1-Day	-0.83	-1.25	-2.29**	-1.11
	2-Day	-0.83	-1.23	-2.12**	-1.06
	3-Day	-0.83	-1.22	-2.06**	-1.05
	4-Day	-0.83	-1.20	-2.03**	-1.03
	5-Day	-0.82	-1.18	-1.99**	-1.00
500-Day	1-Day	0.77	0.26	-1.43	0.44
	2-Day	0.77	0.27	-1.17	0.50
	3-Day	0.77	0.29	-1.08	0.52
	4-Day	0.77	0.30	-1.02	0.53
	5-Day	0.78	0.32	-0.96	0.55

* Significant at 0.10 level
** Significant at 0.05 level
*** Significant at 0.01 level

Figure 15. Time Plots of the Forecasted Dynamic Out-of-Sample Correlations between the Log Returns of the Peso-Dollar Exchange Rate and the Philippine Stock Exchange Index from January, 2009 to February, 2010 using the Mean-Reverting and Integrated Dynamic Conditional Correlation Models, Constant Conditional Correlation Model, Diagonal VECH Model, and Diagonal BEKK Model

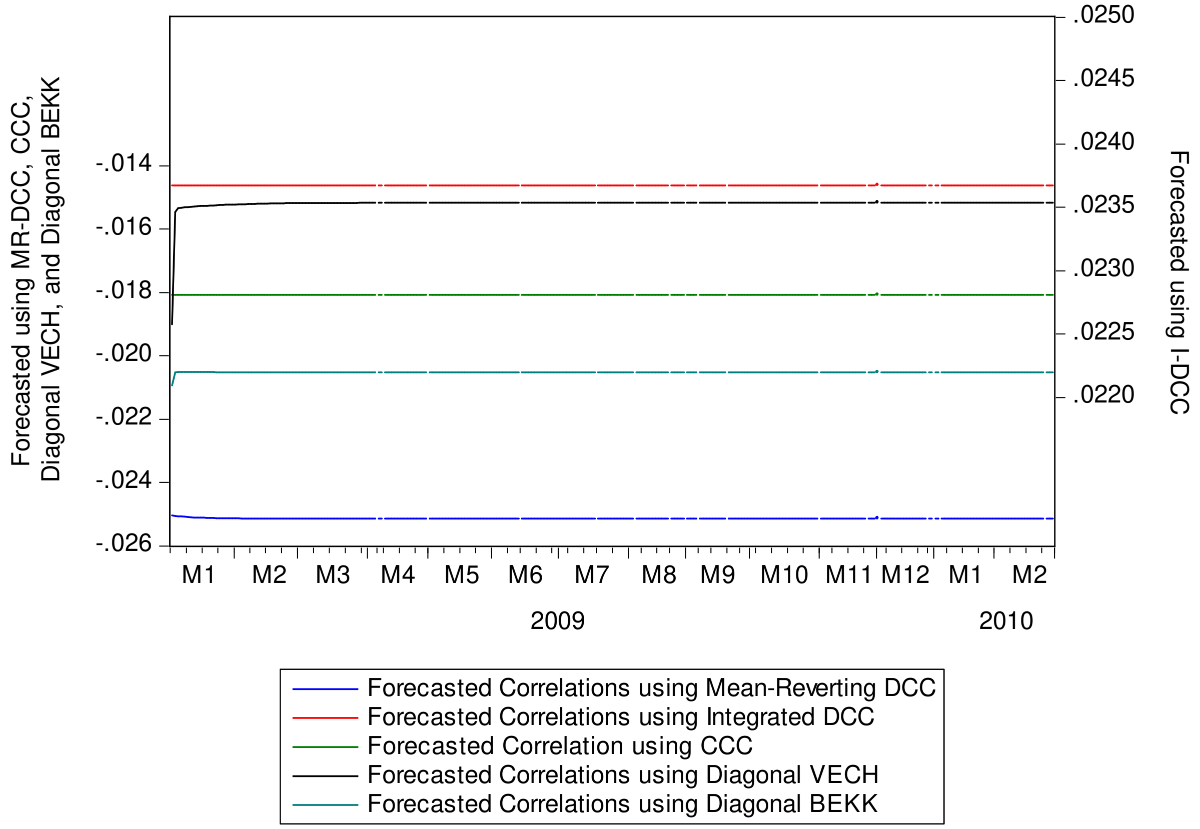


Table 8. Dynamic Forecasting Performance of the Mean-Reverting DCC, Integrated DCC, CCC, Diagonal VECH, and Diagonal BEKK Models as Compared to the 22-Day, 60-Day, 125-Day, 250-Day, and 500-Day Realized Correlations

Date: 04/01/11 Time: 11:25
Forecast Sample: 1/05/2009 2/26/2010
Method: Dynamic
Included Observations: 278

Correlation Proxy	Forecast Error Measures	MR-DCC	I-DCC	CCC	VECH	BEKK
	RMSE	0.245210	0.269657	0.248304	0.249640	0.247216
	MAE	0.205071	0.224459	0.207450	0.208499	0.206593
	MAPE	159.5745	163.6469	141.2357	133.9240	147.4181
22-Day	THEIL	0.869337	0.960974	0.902901	0.917384	0.891018
	Biasprop	0.181731	0.323352	0.201973	0.210290	0.194920
	Varianceprop	0.818212	0.676648	0.798027	0.787859	0.804889
	Covarianceprop	5.64E-05	NA	1.31E-17	0.001851	0.000191
	RMSE	0.144558	0.181763	0.149528	0.151617	0.147787
	MAE	0.127133	0.160191	0.131242	0.132964	0.129816
	MAPE	129.4439	149.8587	118.1320	113.7022	122.0401
60-Day	THEIL	0.768580	0.973934	0.825999	0.851108	0.805497
	Biasprop	0.478273	0.669987	0.512363	0.525582	0.500804
	Varianceprop	0.521628	0.330013	0.487637	0.472183	0.498956
	Covarianceprop	9.97E-05	NA	1.88E-17	0.002235	0.000240
	RMSE	0.108407	0.150095	0.114089	0.116473	0.112104
	MAE	0.087654	0.134803	0.093882	0.096601	0.091590
	MAPE	83.59381	152.2641	85.53014	87.08934	84.22336
125-Day	THEIL	0.702185	0.981481	0.774396	0.806367	0.748492
	Biasprop	0.629301	0.806608	0.665276	0.678546	0.653299
	Varianceprop	0.370607	0.193392	0.334724	0.318911	0.346423
	Covarianceprop	9.17E-05	NA	1.78E-17	0.002543	0.000278
	RMSE	0.064424	0.107321	0.070153	0.072576	0.068141
	MAE	0.051093	0.099878	0.058132	0.061019	0.055685
	MAPE	57.18574	140.4112	69.14957	74.05804	64.97343
250-Day	THEIL	0.581134	0.980982	0.675845	0.719174	0.641341
	Biasprop	0.628470	0.866103	0.686638	0.706867	0.667836
	Varianceprop	0.371362	0.133897	0.313362	0.289343	0.331726
	Covarianceprop	0.000168	NA	3.09E-17	0.003790	0.000438
	RMSE	0.037192	0.084340	0.043787	0.046532	0.041485
	MAE	0.034299	0.083104	0.041358	0.044245	0.038911
	MAPE	55.13589	142.2632	67.73576	72.87891	63.36843
500-Day	THEIL	0.431072	0.994338	0.552738	0.609584	0.507989
	Biasprop	0.850488	0.970915	0.892097	0.904104	0.879772
	Varianceprop	0.149334	0.029085	0.107903	0.092493	0.119796
	Covarianceprop	0.000177	NA	2.80E-17	0.003403	0.000432