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Volatility, Time Varying Correlation and International Portfolio Diversification: An Empirical Study of Australia and Emerging Markets

Gupta. R
School of Commerce, Faculty of Business & Informatics
Central Queensland University, Bruce Highway, Rockhhampton, QLD 4702, Australia
E-mail: R.gupta@cqu.edu.au
Tel: +61749309158; Fax: +61749309700

Mollik. A. T
School of Commerce & Marketing, Faculty of Business & Informatics
Central Queensland University, Bruce Highway, Rockhampton, QLD 4702, Australia
E-mail: a.mollik@cqu.edu.au
Tel: +61749309441; Fax: +61749309700

Abstract

This paper examines the changing correlations between the equity returns of Australia and the emerging equity markets and the tests the volatility, as a factor, that may cause the correlations to change over time. Linear regression estimates of Asymmetric Dynamic Conditional Correlation Model, which allows correlations to change, have been used to test if the volatilities of individual markets or their relative volatility causes the change in correlations.

The results suggest that the correlations between Australia's equity return and emerging markets' equity returns, represented by the respective market index returns, change over time and the variation in correlations is influenced by the volatility of the emerging market returns. In some cases, the relative volatility of the markets, the ratio of emerging market volatility to the volatility of the Australian market, is found to influence the change in correlations. The relationship between the correlations and the volatilities is stronger in some country pairs (with Brazil, Chile, India, Malaysia and Philippines) and very weak for Sri Lanka and Turkey.

JEL Classification Codes: F37, F21, G11 and G15

Introduction and Background

By diversifying his/her portfolios internationally a portfolio manager aims to achieve an optimal risk-return trade-off in investment. The benefits of international diversification depend on the correlations between the returns of the domestic and the foreign assets. Correlations in international equity returns have been known to change over time (Erb, Harvey and Viskanta 1994; Longin and Solnik 1995). Intuitively, the correlations in equity returns should be increasing as the integration proceeds in segmented markets (Bekaert and Harvey 2002). The research in the diversification area has also looked at the differences in benefits of diversifying from or into smaller markets. These benefits arise from the localisation of economic activity and economic specialisation as expected by international trade theory

(Bernstein and Weinstein 1998) and from the segmentation of emerging markets from the more developed markets (Bekaert and Harvey 2000 and 2002; Schmukler 2004; Ibrahim 2006).

The relative structural difference between Australia and emerging markets, and the ongoing changes in the structures of these markets, may cause changes in the relative structural differences in the markets. These changes in the relative market structure between Australia and emerging market pair can influence the correlations between the market returns between Australia and emerging market pairs. This means that the assessment of the changing correlations between equity returns of Australia and emerging markets is important.

Research in the area of portfolio management has also looked into the factors which may drive the changes in the correlations over time. Jithendranathan (2005) tests whether macroeconomic factors can cause changes in correlations in equity returns for the USA and Russian equity markets. He finds that interest rate spread, change in exchange rates and change in energy price index had statistically significant relationship with the correlations between two market returns. Loretan and English (2000) test the relationship between volatility and correlations for equities, bonds and foreign exchange. They find that a significant proportion of the changes in correlations over time are explained by the differences in sample volatilities. However, some authors have looked at this relationship from the perspective of contagion only, e.g. Forbes and Rigobon (2002) look at the volatility and evidence for contagion[1].

In this study we focus on the volatility because from a theoretical standpoint volatility is a measure of total risk of the expected returns of the asset and when the movements of the random variables are more volatile, sample correlations between these variables are expected to increase, despite the principal processes generating the variables remain unchanged (Boyer, Gibson and Loretan 1999). Good quality high frequency data for volatility is readily available and this timely availability of data makes the results meaningful as compared to macroeconomic factors. The problem of data availability for macroeconomic variables is further exacerbated in case of the information for the emerging markets. It is important to note that our study period includes both crisis and boom.

To date, various models have been used to measure the correlations between asset returns. The present study uses Asymmetric Dynamic Conditional Correlation Model (ADCC model), a specific class of multivariate GARCH models, to estimate pair-wise time varying correlations between Australian and emerging markets. Use of the Asymmetric DCC GARCH model for estimation of conditional correlations is strongly supported by theory (Cappiello, Engle and Sheppard 2006). Purpose of using a more complex model for estimating correlations is to arrive at an estimate of correlations that is expected to give a correlations estimate which is closer to the expected future correlations. The Asymmetric DCC GARCH model allows for the revision of correlation estimates based on immediate past conditional variances and the asymmetric effects, thus producing more accurate estimates of correlations.

For the relationship between volatility and correlations we start with Forbes and Rigobon (2002) argument which is based on the observation that heteroskedasticity can cause bias in correlation coefficients. They argued that higher volatility in the period of crises can cause higher correlations because of the bias, but they do not find evidence of contagion with the US market during the crises in Mexico and Hong Kong. Yoon (2005), however, following the same argument of Forbes and Rigobon (2002), but using a stochastic unit root process finds that the lower (higher) volatility causes the correlations coefficients to move upwards (downward). The present study finds support for this finding as the results reveal that decrease in volatility is negatively related with the correlations in equity returns. This statistically significant inverse relationship suggest that if the volatility of the returns keeps decreasing, correlations in equity returns are expected to increase, thereby reducing the benefits associated with diversifying into emerging markets. However, our result is based on a computationally efficient model for estimating the correlations that are more relevant for portfolio optimisation. The

[1] Contagion refers to the transmission of shocks across markets that are over and above that is expected through fundamental linkages (Dungey, Martin and Fry 2006)

result also demonstrates that changes in volatility of the underlying asset can cause the changes in correlations between different market returns over time.

We address two key issues in this paper. Firstly, we examine the dynamics of the correlations; assessment of the correlations is important for a funds manager and that becomes more important for an Australian investor because of the structural differences between Australia and emerging equity markets[2]. This is the first study that examines the correlation dynamics of the Australian equity returns with that of the emerging market returns using a model that allows for correlations to change over time. Secondly, we test for volatility as the factor that may cause these changes in correlations over time. Higher volatility of emerging markets and the financial crisis has often been cited as two of the reasons for portfolio managers to shy away from emerging equity markets[3]. Understanding of this linkage may be of interest to fund managers who seek to benefit from diversifying into emerging equity markets. In this study, we use a computationally efficient method of estimating the correlations and test to see if change in volatility causes the correlations to change over time.

Investment into foreign equities can increase benefits of portfolio diversification as compared with the domestic portfolio. In the context of portfolio theory the benefits from diversification depend on the correlations between the assets within the portfolio. In the case of international diversification this will depend on the correlations between domestic and foreign securities. Thus, understanding the correlation dynamics of the equity returns is important to the portfolio managers. Some studies (Erb, Harvey and Viskanta 1994 and Longin and Solnik 1995) found the correlations in international equity returns to change over time. These changes in correlations will in turn influence the potential diversification benefits into foreign equities over time.

Methodology

Different techniques have been used in measurement of time varying correlations. The most common method used is a moving average specification. In this method correlations are estimated by using a specific window of time (number of days, weeks or months). The primary weakness of this method is that it gives equal importance to all observations within the time period used in the moving average calculations. The other method of estimating correlations is to use multivariate GARCH models. The initial models in this group were based on the Constant Correlation Coefficient model of Bollerslev (1990). These models were based on the assumption that the correlations coefficients are constant over time, which is unrealistic; this was the main weakness of the models of this class. The second set of GARCH models used in this context is based on the multivariate GARCH models introduced by Kroner and Ng (1998). Although theoretically appealing, these models were computationally complex because of the need for estimating a large number of coefficients at the same time. Engle (2002) introduced multivariate GARCH models called “Dynamic Conditional Correlation Models”, which combined flexibility of the univariate models with the theoretical power of time varying correlations. This model is used by Jithendranathan (2005) in his study on changes in correlations between the US and Russian equity markets.

The Dynamic Conditional Correlation Model (DCC GARCH) of Engle (2002) permits asymmetries in variances, but not correlations, and is developed on the argument that any univariate GARCH model which has stationary covariance and assumes that errors are normally distributed (irrespective of the factual distribution) can be used to model variances. The model is estimated in two steps: the first step estimates variances using a univariate GARCH specification and then parameters of dynamic correlations are estimated. Sheppard (2002) extended the DCC model to allow for asymmetric dynamics in the correlations along with asymmetric dynamics in variances. Cappielo, Engle and Sheppard (2006) used this in their study of asymmetric dynamics in the correlations of global and bond

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[2] For a review of literature on benefits of diversifying into emerging markets see Bekaert and Harvey (2002) and Gupta (2006) for a review of literature on differences in Australian and emerging equity markets and their impact on diversification benefits for Australian investors.

[3] Ibid.

equity returns.[4] The authors find considerable evidence of asymmetries in conditional covariance of both equity and bond returns. Further, the asymmetries are present in different ways in different markets. Evidence recommends the use of the asymmetric GARCH model for estimating conditional correlations as against the use of the standard multivariate GARCH model that does not allow for asymmetric dynamics in correlations.

In this study we estimate the time varying correlations using the Asymmetric Dynamic Conditional Correlation (DCC) model of Cappielo, Engle and Sheppard (2006). This model is an introduction of the asymmetric term into the original DCC model of Engle (2002) as modified by Sheppard (2002) as a general model. Many methods have been used to estimate correlations, initially unconditional correlations were used that ignored that correlations change over time. Another commonly used method is to use a rolling estimator, where the unconditional means, variances and co-variances are estimated using a rolling window of a fixed number of observations over the sample period. The main weakness of this method is that it does not capture the time varying nature of the means, variances and co-variances. As discussed in the preceding section, a number of multivariate GARCH models were introduced to estimate time varying correlations. These models were complex and time consuming because the number of parameters needed to be estimated were large. As such most papers considered only five assets despite the apparent need for much larger correlation matrices.[5] Next development in the series of multivariate GARCH models was the introduction of 'Dynamic Conditional Correlation' model of Engle (2002)[6]. Main weakness of this model is its two step estimation process that was introduced to make it easier to estimate. However, the two step estimation process requires that the correlation processes are restricted to same dynamic structure[7]. Another weakness of the original DCC model was in ignoring the asymmetric effects in the initial model. This weakness has been overcome in the current model (ADCC GARCH model which is used in this study). In general when time varying volatility is not important the relative advantages of the DCC model is reduced and DCC model is difficult to estimate for a shorter[8] series because of convergence problems. Model developed by, Engle and Sheppard (2006) overcomes the problem of asymmetry. We use this model for the analysis. Two-step estimation causes some efficiency losses, but makes it easier for estimation of more number of parameters together. Engle (2002) reviewed the performance of the multivariate GRACH models in his paper and find that the DCC GARCH model is a good approximation.

> The comparison of DCC with simple multivariate GARCH and several other estimators shows that the DCC is often the most accurate. [.] Statistical tests on real data indicate that all these models are miss-specified but that the DCC models are competitive with the multivariate GARCH specifications and are superior to moving average methods.
> (Engle 2002, p. 348)

Similar results are reported by Wong and Vlaar (2003). Jithendranathan (2007) in a comparison of ex post performance of the optimised portfolios finds that the portfolios constructed with correlations estimated using DCC model yields better results as compared with the rolling estimator.

The Correlation Model

The conditional correlation between two random variables r_1 and r_2 that have mean zero can be written as:

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[4] Cappielo, Engle and Sheppard (2006) have explained the economic rationale of asymmetric volatility on the basis of two models: leverage effect and time varying risk premia (volatility feedback).

[5] The number of potential assets that could be included in an optimised portfolio will be significantly more than five assets used in the studies using alternative models and will make it harder to estimate these multivariate GARCH models.

[6] Robert Engle was awarded Nobel Prize in 2003 for his work *'for methods of analysing economic time series with time-varying volatility (ARCH)'*.

[7] Model can be estimated in a single step which makes the estimation process slower and more complex.

[8] A series of above 400 data points is recommended for DCC GARCH models.

$$\rho_{12,t} = \frac{E_{t-1}(r_{1,t} r_{2,t})}{\sqrt{E_{t-1}(r_{1,t}{}^2) E_{t-1}(r_{2,t}{}^2)}} \tag{1}$$

$Let\ h_{i,t} = E_{t-1}(r_{1,t}{}^2)\ and\ r_{i,t} = \sqrt{h_{i,t}\varepsilon_{i,t}}\ for\ i = 1,\ 2,\ where\ \varepsilon_{i,t}$ is a standardised disturbance that has zero mean and a variance of one $\varepsilon_t = D_t^{-1} r_t$;

Substituting the above into equation (1) we get:

$$\rho_{12,t} = \frac{E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t})}{\sqrt{E_{t-1}(\varepsilon_{1,t}{}^2) E_{t-1}(\varepsilon_{2,t}{}^2)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t}) \tag{2}$$

Using GARCH(1,1) specification, the covariance between the random variables can be written as:

$$q_{12,t} = \overline{\rho}_{12} + \alpha(\varepsilon_{1,t-1}\varepsilon_{2,t-1} - \overline{\rho}_{12}) + \beta(q_{12,t-1} - \overline{\rho}_{12}) \tag{3}$$

The unconditional expectation of the cross product is $\overline{\rho}_{12}$, while for the variances $\overline{\rho}_{12} = 1$

The correlation estimator is:

$$\rho_{12,t} \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \tag{4}$$

This model is mean reverting if $\alpha + \beta < 1$. The matrix version of this model is written as:

$$Q_t = S(1-\alpha-\beta) + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1} \tag{5}$$

where S is the unconditional correlation matrix of the disturbance terms and $Q_t = \left|q_{1,2,t}\right|$. The log likelihood for this estimator can be written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log\left|D_t\right| + \log\left|R_t\right| + \varepsilon'_t R_t^{-1}\varepsilon_t) \tag{6}$$

where $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ and R_t is the time varying correlation matrix.

As this model does not allow for asymmetries and asset specific news impact, the modified model which Cappiello, Engle and Sheppard (2006) use for incorporating the asymmetrical effect and the asset specific news impact is:

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'Q_{t-1}B + G'n_{t-1}n'_{t-1}G \tag{7}$$

where A, B and G are diagonal parameter matrixes, $n_t = I[\varepsilon_t < 0] o\ \varepsilon_t$ (with o indicating Hadamard product), $\overline{N} = E[n_t n'_t]$. For $\overline{Q}$ and $\overline{N}$, expectations are infeasible and are replaced with sample analogues, $T^{-1}\sum_{t=1}^{T}\varepsilon_t\varepsilon'_t$ and $T^{-1}\sum_{t=1}^{T} n_t n'_t$, respectively. $Q_t^* = [q_{ii,t}^*] = [\sqrt{q_{ii,t}}]$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position.

Bekaert and Wu (2000) give an empirical framework for analysing the asymmetric volatility in the equity markets and Forbes and Rigobon (2002) develop a relationship between volatility and the correlations. Studies prior to these studies did not address the asymmetric dynamics in the correlations and/or the economic rational for changes in correlations.

According to Bekaert and Wu (2000), a negative shock at the market level produces two effects. Firstly, investors may change their expectations of conditional variance upwards; as this upward movement in conditional volatility at the market level will be rewarded by an increase in returns, the current value of the market will fall. Secondly, the fall in prices across the market will result in an increase in leverage at market level and hence higher stock volatility. The second outcome will cause the volatility feedback[9].

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[9] If volatility is priced, an anticipated increase in volatility would raise the required rate of return, in turn necessitating an immediate stock price decline in order to allow for higher future returns.

The external shock may cause a change in the conditional variances of one or both markets and this change in conditional variances at market levels can result in a change in correlations between the expected returns of the markets. If the influence of the external shock is the same on both the markets, the external shock is not expected to have any impact on the correlations between the expected returns of the two markets. In addition, if the external shock is asymmetrical on the conditional variances, it will cause a change in the correlations. Further, a higher volatility in the random variables can cause the sample correlations between these variables (returns) to increase even if the principal processes that generate the variables remain unchanged; Boyer, Gibson and Loretan (1999) developed this theoretical argument[10]. Loretan and English (2000) use this in their study of the relationship between volatility and correlations. Forbes and Rigobon (2002) find no evidence of contagion with the US market during the financial crises in the Hong Kong and Mexico. Yoon (2005) argued that lower (higher) volatility will cause correlations to move higher (lower) and tested the relationship empirically using a stochastic unit root process. Yoon found that the cross-country correlations have increased after adjusting for lower variability in the US economy over the years. Based on Yoon's (2005)[11] findings, we assume an inverse relationship between volatility of the equity returns and correlations of the market returns.

If the expected risk of an asset changes, it will influence the expected return of that asset and the correlations of the returns of the asset with the returns of the other assets in the portfolio. Since we are using the emerging market indexes for the study, overall change in the country risk may change the risk of the equity market index of the country. To capture the effect of this changing country risk we use the volatility of the returns of the equity market index of the country as one of the variables that can cause the changes in the expected risk of the emerging market equities and subsequently correlation of the returns of the emerging market with the returns of the Australian equities[12]. We test for volatility of the emerging market, volatility of the Australian market and the ratio of the volatility of the emerging equity market to the volatility of the Australian equity market. Following Young and Johnson (2004), we use this ratio as a measure of relative volatility of the two markets.[13] Purpose of using the ratio of the volatilities is to capture the relative volatility measure. Practitioners in the market frequently use the ratio as a measure of the relative volatility of the two markets. Intuitively, this can be compared with the beta as used in the asset pricing. Beta in CAPM is a measure of relative volatility of the particular asset to the market volatility.

We use the following regression model to estimate the factors that may cause the correlations to vary over time:

$$\rho_{i,t} = \alpha_i + \beta_1 Volatility_E + \beta_3 \, {}^{Volatility_E}\!\big/_{Volatility_{AUS}} + \varepsilon_t \tag{8}$$

Where $Volatility_E$ is the volatility of the emerging market equity index and the ${}^{Volatility_E}\!\big/_{Volatility_{AUS}}$ is the ratio of the volatility of the emerging market equity index to the volatility of the Australian market equity index, α is a constant and ε is a random error term, I refers to the individual indexes and t is time.

We also run a regression of correlations as a dependent variable and Australian market volatility as an independent variable; a regression of correlations against volatility of the emerging market and a regression of correlations against relative volatility. Other regression models tested in the study are.

$$\rho_{i,t} = \alpha_i + \beta_1 Volatility_E + \varepsilon_t \tag{9}$$

$$\rho_{i,t} = \alpha_i + \beta_1 Volatility_{Aus} + \varepsilon_t \tag{10}$$

[10] See Boyer, Gibson and Loretan (1999) for a formal proof and Loretan and English (2000) for application of the relationship.

[11] A discussion on Yoon's adjustment and detailed findings are omitted from here for the limitations of space.

[12] Asymmetric DCC GARCH model estimates the conditional correlations based on the conditional variances of the two markets. We run these regressions as a simple test of relationship between the estimated time varying correlations and the unconditional volatility of each market. A test of correlation and volatility has been conducted by Knif and Pynnonen (2007); they use a logit type regression model.

[13] Using volatility ratio as a measure of the relative volatility is common in portfolio management practice; see the explanatory notes on the definition of risk and returns, Fidelity International, www.fidelity.no/docs/business_centre/common/explaination.pdf.

$$\rho_{i,t} = \alpha_i + \beta_1 \frac{Volatility_E}{Volatility_{AUS}} + \varepsilon_t \qquad (11)$$

Data

For this study we use monthly returns of the Australian 'All Ordinaries Index' and the monthly returns of the market indexes in the emerging market countries for the period February 1988 to December 2005. Since the emerging market indexes are either available in US dollars or their respective currencies, for consistency we use the dollar denominated index values for all the indices. Returns are calculated in US dollar terms.

In order to calculate the volatility of the respective index, we use daily prices to calculate the daily returns and the daily average volatility of each market index returns. We calculate monthly volatility ($Volatility_m$ = Daily volatility X $\sqrt{n}$, where m represents period and n number of trading days in the period) of each market on the basis of actual number of trading days in the month for the emerging market. Index values of the respective equity indexes, acquired from DataStream, have been used for Australia, Brazil, Chile, Greece, India, Korea, Malaysia, Mexico, Pakistan, the Philippines, Sri Lanka, and Turkey.

Data for emerging markets is limited and the series for different emerging market countries start at different start dates. Ideally we should have used all the data available, but for consistency we have used the earliest date from which the data is available for most of the emerging market countries. We still have a sufficiently long series of data: the start date for the data is February 1988 and the end date is December 2005[14]. The classification of emerging markets and the developed markets should be based on the theoretical constructs, but in most empirical studies, the distinction is drawn from the World Bank definition of emerging markets and the data suppliers use a similar definition. This study uses the emerging markets used by Bekaert and Harvey (2000)[15]. Reliable and high frequency data for these countries is available and other researchers use a similar sample set. Other countries are excluded from the sample because of one or more of the following reasons: stock markets in those economies are not well developed, reliable high frequency data is not available, or foreign investors do not have direct access to the shares and other assets in those countries.

In this study of correlations, dynamics of the monthly returns of twelve of the emerging market indexes with the Australian index are calculated using the Asymmetric Dynamic Conditional Correlation Model. The period of this study covers February 1988 to December 2005. Table 1 lists the market returns and summary statistics for the markets that form the study sample. There are 215 observations for each market, except Pakistan that has a shorter series with 204 observations. The mean returns for Australia is 0.006% per month and for emerging markets the mean returns range from 0.008% for Sri Lanka to 0.033% for Brazil. The monthly variance for emerging markets ranges between 0.004 for Chile and 0.039 for Brazil as against 0.001 for the Australian market.

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[14] We use the monthly data for the period 1988 to 2006 for the GARCH estimates; for some countries this data set starts at a later date. For the volatility estimates the starting date is chosen as February 1988 and the ending date as December 2005 because of the availability of the daily data. Here, for consistency we present the results for correlations for the period up to December 2005.

[15] They look at the impact of market liberalisation on the domestic markets and we look at the correlations between the market pairs between Australia and emerging market pairs.

Table 1: Summary statistics of the returns data for the sample

Market	Obs.	Mean	Skewness	Kurtosis	Jarque-Bera	Variance	Minimum	Maximum
Australia	215	0.006	-0.270	-0.056	2.648	0.001	-0.102	0.105
Brazil	215	0.033	0.832	3.598	140.8	0.039	-0.669	0.954
Chile	215	0.013	0.207	0.098	1.624	0.004	-0.178	0.230
Greece	207	0.014	1.441	4.612	255.1	0.011	-0.233	0.524
India	215	0.011	0.546	0.884	17.73	0.008	-2.218	0.374
Korea	215	0.011	1.184	3.968	191.3	0.011	-0.282	0.556
Malaysia	215	0.008	0.595	4.662	207.4	0.008	-0.298	0.492
Mexico	215	0.022	0.200	3.701	124.1	0.011	-0.371	0.553
Pakistan	204	0.013	0.318	2.384	51.78	0.010	-0.386	0.442
Philippines	215	0.009	0.563	3.310	109.5	0.008	-0.274	0.454
Sri Lanka	215	0.008	0.502	1.090	19.69	0.006	-0.205	0.358
Turkey	215	0.023	1.046	2.481	94.40	0.037	-0.449	0.811

Results

We start the analysis with an estimate of unconditional correlations between these markets. Table 2 below shows unconditional correlations of the Australian equity returns with the equity returns of the emerging markets.

Table 2: Average correlation of Australia with emerging markets during different periods based on raw returns.

	1988 to 1998	1998 to 2005	1988-2005
Brazil	0.271	0.504	0.308
Chile	0.006	0.305	0.066
Greece	0.192	0.132	0.178
India	-0.028	0.431	0.092
Korea	0.164	0.548	0.257
Malaysia	0.250	-0.019	0.190
Mexico	0.275	0.632	0.342
Pakistan	0.083	0.061	0.075
Philippines	0.304	0.205	0.284
Sri Lanka	0.012	-0.035	0.000
Turkey	0.086	0.354	0.153
Median	**0.164**	**0.305**	**0.178**

As seen in Table 2, the average correlations of Australian equity returns with emerging market returns for the period 1988 to 2005 are as low as 0.000 with Sri Lanka and up to 0.342 with Mexico. If we partition the data into different periods, 1988 to 1998 (time of the Asian crisis) we see that Australia has lowest correlations with Sri Lanka but highest correlations with Brazil and not with Mexico. In the period 1998 to 2005 correlations with Pakistan are still lower, i.e. 0.061 (slightly lower than for the 1988 to 2005 and the 1988 to 1998 period). After the split the higher correlations are with India, i.e. 0.431, much higher than for the full sample period and the sub-sample of the 1988 to 1998 period. Similarly, in the case of Brazil the correlations for this period rise to 0.504 from the 0.308 for the period 1988 to 2005 and 0.271 for the period 1988 to 1998. Correlations with Malaysia fell to -0.019 from a high of 0.190 for the period 1988 to 2005 and 0.250 for the period 1988 to 1998. Median correlations between Australia and emerging markets increased from 0.164 for the period 1988-1998 to 0.305 in 1998-2005.

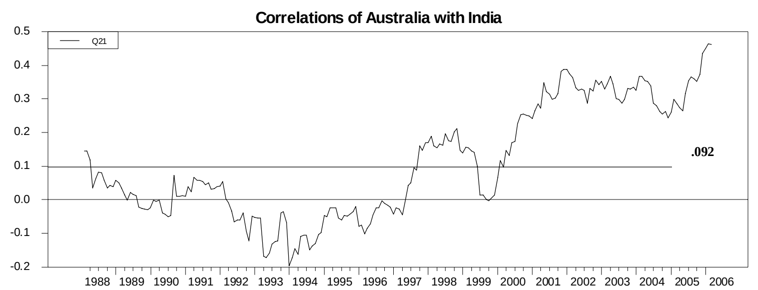
These results show that the correlations of Australian equity returns with different emerging equity market returns are changing over the period (1988 to 2005) and that the change is not uniform. With some emerging equity markets the correlations have increased, for example Brazil as reflected in the table above increased from 0.271 in 1988 to 1998 to 0.504 in 1998 to 2005, and during the same period the correlation with Malaysia fell from 0.250 to -0.019.

We further estimate these time varying correlations using the Asymmetric DCC GARCH model[16] and the graphs in Annexure 1 show the changes in the correlations over the full sample period. Results from the Asymmetric DCC model as given in Table 3 show that the correlations in the markets have a significant relationship with the lagged conditional variances (t-statistic is significant at 1% level in most markets) and with lagged squared error term in some markets. The asymmetric term is only significant in Korea, Pakistan and the Philippines at 1%.

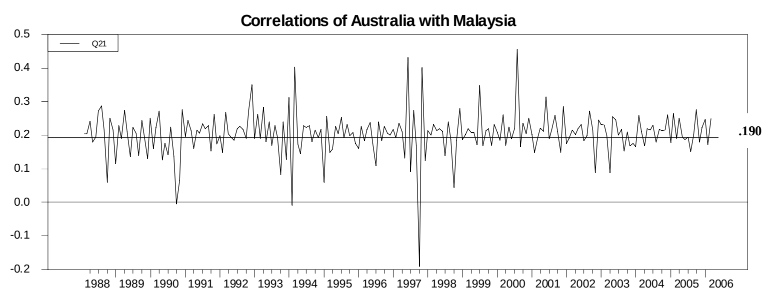
The following two graphs (Figure 1) show the different patterns of changes in correlations for Australian equity returns with the emerging market equity returns. Results for other markets are given in Annexure 1. Unconditional correlations are marked on the graphs as a straight line to show the comparison of unconditional correlations with time varying correlations.

Figure 1: Time varying correlations for Australia vs. emerging markets.

Australia and India



Australia and Malaysia



Australian equity returns with Malaysia fluctuate over the period with no apparent trend, whereas Australian correlations with India increase over the period. The graphs for the correlations for the period 1988 to 2005 between Australia and emerging market pairs are given in Annexure 1. The effect of the Asian financial crisis of 1997-98 on the countries that were affected by the crisis can be seen in the graphs as extreme fluctuations in the correlations around the crisis period. This accurate estimate of correlations and the understanding of changes in correlations over time can help the investor make informed decisions and enhance the risk adjusted expected returns of his/her internationally diversified portfolio. Table 3 presents the results of Asymmetric DCC GARCH coefficient estimates.

Study of variation in correlations over time in equity markets is a new area and has recently emerged with the development of advanced GARCH models. Jithendranathan (2005) finds that the correlations of US equity returns with Russian markets change over time. He finds a statistically significant relationship between the correlations and changes in energy prices, interest rate spreads and exchange rates.

[16] We use RATS 6.2 software by Estima for our estimation purposes.

The results show the wide differences in correlations with the emerging equity markets for Australia. They also show that the correlations fluctuated in a wide range with a low of -0.6426 in January 1994 with Greece and a high of 0.8921 with Mexico in October 1998. In general the correlations were lowest with the emerging markets around 1988 (the beginning of the sample)[17] and highest in 1997 and 1998, the period of the Asian crisis. The Asian crisis caused a rapid outflow of capital from the Asian countries[18]. This simultaneous withdrawal of funds from the Asian markets could have caused the correlations in the equity markets to increase during the period. Table 3 shows the Asymmetric DCC GARCH estimates and Table 4 shows the correlations of Australia with emerging markets as estimated at the end of the sample period. Coefficients of Asymmetric DCC GARCH are significant at 1% level for the lagged conditional variances in most markets, which suggests that the lagged conditional variances have a significant association with the correlations. Coefficients for the asymmetric term in most cases are not significant, suggesting asymmetries in correlations do not significantly influence the correlations between the equity returns. Results for the lagged squared error term are mixed.

Table 3: Asymmetric DCC GARCH estimates of Australian vs. emerging market returns.

Coefficients	**Brazil**	**Chile**	**Greece**	**India**	**Korea**	**Malaysia**
Lagged squared error	0.0213	0.0365	0.1185	0.0309	-0.0381	-0.0523
t-statistics	1.1327	0.5529	1.5099	1.5613	-556.51*	-5.2902*
Lagged conditional variance	0.9735	0.9497	0.0379	0.9652	-0.3919	-0.2569
t-statistics	37.344*	18.420*	0.2996	203.13*	-2233.1*	-1.0334
Asymmetric term	0.0493	-0.0555	-20.2127	0.0337	0.1141	-0.7874
t-statistics	1.1651	-0.1231	-0.2140	0.5001	556.62*	-1.4320
	Mexico	**Pakistan**	**Philippines**	**Sri Lanka**	**Turkey**	
Lagged squared error	0.0412	-0.0379	-0.0383	-0.0474	0.0813	
t-statistics	2.3206**	-36.990*	-1.7059**	-1.0692	1.1034	
Lagged conditional variance	0.9630	-0.6550	-0.4246	-0.6177	0.6106	
t-statistics	73.905*	-2.7677*	-1.3961	-0.2504	12.666*	
Asymmetric term	-0.0129	0.0734	0.1731	0.0944	-1.2918	
t-statistics	-0.0960	12.012*	2.9470*	0.1593	-0.5244	

* significant at 1%, ** significant at 5% and *** significant at 10% level.
t-statistics are based on robust standard errors.

Log-likelihood function maximised under normality assumption for the disturbances is:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t)$$

From equation 7, $\overline{Q}$ is the unconditional covariance of the standardised residuals resulting from the first stage estimation, and

$$Q_t^* \begin{bmatrix} \sqrt{q11} & 0 & 0 & \ldots & 0 \\ 0 & \sqrt{q22} & 0 & \ldots & 0 \\ . & . & . & . & . \\ 0 & 0 & 0 & .. & \sqrt{qkk} \end{bmatrix}$$

so that Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Qt

[17] 1988 is widely considered to be the time when globalisation started in most emerging markets.
[18] Gupta and Basu (2007) review the literature on the Asian crisis and Chapter 3 documents the export of Australian investment into emerging markets.

Table 4: Comparison of ADCC correlations with unconditional correlations of Australian equity returns with emerging market equity returns.

	ADCC Correlations	1988 to 1998	1998 to 2005	1988-2005
Brazil	0.481	0.271	0.504	0.308
Chile	0.275	0.006	0.305	0.066
Greece	0.196	0.192	0.132	0.178
India	0.436	-0.028	0.431	0.092
Korea	0.352	0.164	0.548	0.257
Malaysia	0.222	0.250	-0.019	0.190
Mexico	0.329	0.275	0.632	0.342
Pakistan	0.098	0.083	0.061	0.075
Philippines	0.315	0.304	0.205	0.284
Sri Lanka	0.100	0.012	-0.035	0.000
Turkey	0.240	0.086	0.354	0.153
Median	**0.275**	**0.164**	**0.305**	**0.178**

Second column gives correlations of Australian equity returns with emerging markets calculated using Asymmetric DCC model and columns three; four and five shows unconditional correlations for different sample periods.

A comparison of DCC correlations with the simple correlations shows that the DCC correlation estimates do not have the extreme correlations that were present in the simple correlations; e.g. correlations for India for the period 1988 to 2005 are 0.092 and if we estimate this using a sample period of 1998 to 2005 the correlation coefficient is 0.431 and for Malaysia the estimate for 1998 to 2005 period is -0.019. As numeric comparison of two correlation estimates is difficult, we present the unconditional correlation estimates on the graphs of the conditional correlations in Annexure 1. It is evident from seeing the graphs that the correlations deviate substantially from the point estimates of the unconditional correlations and in most cases the unconditional correlations are different from the correlations as estimated by Asymmetric DCC GARCH correlations.

As discussed in the review of literature (see Chapter 2), in the classic portfolio theory diversification benefits depend on the correlations between the domestic and the foreign assets. An accurate estimate of the correlations can significantly help in improving the returns for a portfolio manager by switching the international portfolio between different emerging market indexes over a period, based on the estimates of the correlations of each market. If unconditional correlations are used to construct an optimised portfolio and the true estimates of the correlations are the ones estimated by the Asymmetric DCC GARCH model, the resulting optimal portfolio will not represent the potential benefits of diversification.

To understand the factors that may influence the correlations and changes in correlations over a period, we run regressions for up to two lags of all independent variables. Independent variables are: volatility of the Australian market (Aus), volatility of the emerging market (e.g. Arg, Brz, Chi) and the ratio of the emerging market volatility to Australian market volatility (Ratio). The dependent variable for the study is correlations between the two markets, the Australian equity market and the emerging equity market. In the next step we run a stepwise regression for up to two lags to identify[19] the best fit model for the data using only emerging market volatility and the ratio. The results of stepwise regression are similar to the ones using the selection of variables based on intuition. Below we present the results of the stepwise regression.

[19] Manera, McAleer and Grasso (2006) find two lags to be important in their study of volatility of oil spots and futures.

Table 5: Regression results of factors affecting the correlation between Australian returns and emerging market returns (Asymmetric DCC GARCH)

Regression Equation: $\rho_{i,t} = \alpha_i + \beta_1 Volatility_E + \beta_2 \frac{Volatility_E}{Volatility_{AUS}} + \varepsilon_t$

Market	Variable(Lags)	Coefficients	T-stat	No. of observations	Adj. R^2 (Uncentred R^2) (DW-Statistic)	(Significance level of F)
Brazil	Brzvol	-0.6175	-2.6130*	213	0.0548	0.0096
	Ratio(1)	-.0036	-1.6453***		-	0.1014
					(0.1367)	0.0009
Chile	Chivol	-13.9893	-5.2290*	213	0.2572	0.0000
	Chivol(1)	-5.6854	-2.4075**		-	0.0169
	Chivoll(2)	-6.2216	-2.8554*		(0.2042)	0.0047
	Ratio	0.0784	4.2812*			0.0000
						0.0000
India	Indvol	-6.7991	-3.0788*	213	0.0482	0.0023
	Ratio	0.0493	3.4472*		-	0.0006
					(0.2787)	0.0020
Malaysia	Malvol(1)	-1.9334	-4.9926*	213	0.0986	0.0000
	Ratio(2)	0.0126	2.9184*		-	0.0039
					(1.7257)	0.0000
Mexico	Mexvol	-0.9948	-1.7857**	213	0.0910	0.0755
	Ratio	0.0150	3.1808*		-	0.0016
	Ratio(2)	0.0103	2.9563*		(0.1333)	0.0034
						0.0000
Philippines	Phivol(1)	-7.4018	-3.7599*	213	0.0738	0.0002
	Ratio(1)	0.0645	4.1295*		-	0.0000
					(0.3512)	0.0001

* significant at 1%, ** significant at 5% and *** significant at 10% level. Variables are: Brzvol means volatility of Brazil market (emerging market), Ratio means ratio of volatility of emerging market to Australian market volatility. Terms in brackets represent the lags.

As expected in the theory [20], the signs of the coefficients are negative (see Introduction, p. 5), that is, as the volatility decreases the correlations should increase and vice versa. Signs of the coefficients in other regressions estimated (as given in Annexures 3 and 4) are also consistent with this. Signs for the relationship between the relative volatility and correlations are positive in cases where Australian volatility shows a stronger relationship with the correlations and not with the emerging market volatility.

Regression results show that in the markets of Chile, Korea, Malaysia and Mexico the adjusted R square is close to 0.1 or above, suggesting that some proportion of the variation in the correlations is explained by the independent variables (volatility of the emerging market or relative volatility of these markets). For the markets of Brazil, Greece, India, the Philippines, Sri Lanka and Turkey, adjusted R squared is lower than the former group of countries but significant enough to suggest a relationship between the independent variables (volatility of emerging market and the relative volatility of the two markets) and the dependent variable (correlations between the two markets). Results for Brazil, Chile, India, Korea, Malaysia, Mexico and the Philippines are significant at 1% for most independent variables and 5% for some independent variables in the respective markets. In general, results suggest that the volatility of the emerging market is important for the correlations between equity returns of Australia and emerging market pairs.

The regression results suggest that the volatility of the emerging market may have influenced the correlations between the emerging market equity returns and Australian equity returns. Relationship with emerging market volatility is significant in all at 1% level with zero lag or one lag (in the case of Malaysia, the Philippines and Chile; in the case of Chile it is significant with all lags) except Mexico. For relative volatility the results are weaker, with one or two lags. The last column of Table 5 shows an overall significance level of 'F'. This can be interpreted as meaning that the chance

[20] See page 13.

that the results could be random is less than 1% (at a given confidence interval). Individual P values for each independent variable in regressions is low interpreting this together with the overall P value of the regression suggest that multicollinearity should not a reason for concern. A Bonferroni[21] correction for multiple regressions is a conservative test and is applied by dividing the test-wise significance level by the number of tests. This suggests that the results are significant at a 5% significance level for Brazil and at a 1% significance level for the rest of the markets. Durbin-Watson test for serial correlation suggests presence of serial correlations in all the markets at 5% level. Serial correlation is not expected to be of concern for the study as the lags of the explanatory variables have been included in the regression. Results for the excess kurtosis and Jarque-Bera statistic for the series are given in Annexure 5; these statistics show that some of the series are not normally distributed. In these markets (Brazil, Malaysia and Mexico) we identify the outliers and run the regressions with a dummy variable. We find very similar results with the dummy variable.

The results for other regressions estimated are given in Annexures 2 to 4. Annexure 2 shows the regression results for correlations and volatility of emerging markets; Annexure 3 for correlations and the Australian market; Annexure 4 for correlations and the relative volatility between Australia and emerging market pairs. These results show that in most markets the correlations show a relationship with the volatility of the emerging markets and the relative volatility and a weak relationship between the correlations and the volatility of the Australian market.

The time lag in this study represents the delay in transmission of volatility information (independent variable) to the correlations (dependent variable). The results show that lags of independent variables are important and the speed of transmission of information is different in different markets. Different information transmission speeds in different markets could be the result of stages of integration of these markets with the global markets in general and Australian market in particular. Another factor that can explain different speed of information transmission could be market efficiency of the individual stock markets. Most emerging stock markets are considered to be not weak form efficient and poor market efficiency could cause these markets to respond slower to changes in the market factors. However, test of these factors is beyond the scope of this study.

Conclusion

This paper addresses the changing correlations between the equity returns of Australia and emerging market pairs and tests for the factors that may cause the correlations to change over time. We use a computationally efficient DCC GARCH model for estimating time varying correlations. A significant contribution of this study is the relaxation of the condition of symmetry in the estimate of the GARCH model.

We find that the correlations of Australian equity returns with emerging market pairs change over time. We also find that the changes in correlations between Australia and individual emerging market pairs are not uniform. Correlations with some emerging markets, e.g. Malaysia, fluctuate around the mean, while with India and Brazil the correlations in general have increased over the period of time and with Malaysia and the Philippines they are very volatile. Use of Asymmetric DCC GARCH model is theoretically recommended for estimating correlations as the model effectively captures the time varying nature of the correlations and gives more reliable estimate of correlations as compared with the unconditional estimate of correlations.

The regression results indicate a relationship between the volatility of the emerging market equity returns, the relative volatility of the emerging markets equity returns and the Australian market equity returns with the correlations for Brazil, Chile, Greece, India, Korea, Malaysia, Mexico and the Philippines. The relationship for some markets is stronger than for others. For Sri Lanka and Turkey the relationship is very weak and for Pakistan the results show no relationship. The results also show

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[21] Bonferroni correction at times has been criticised for being too conservative and testing each individual test to an unreasonably high standard of acceptability.

that there is a time lag in the transmission of influence of volatility and/or relative volatility into the correlations.

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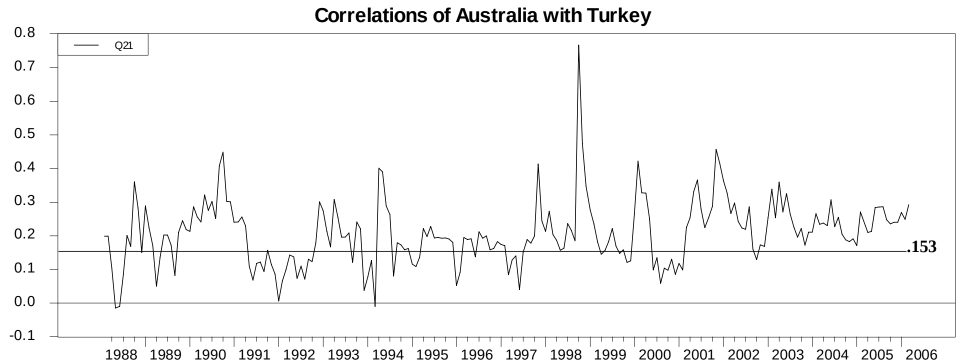
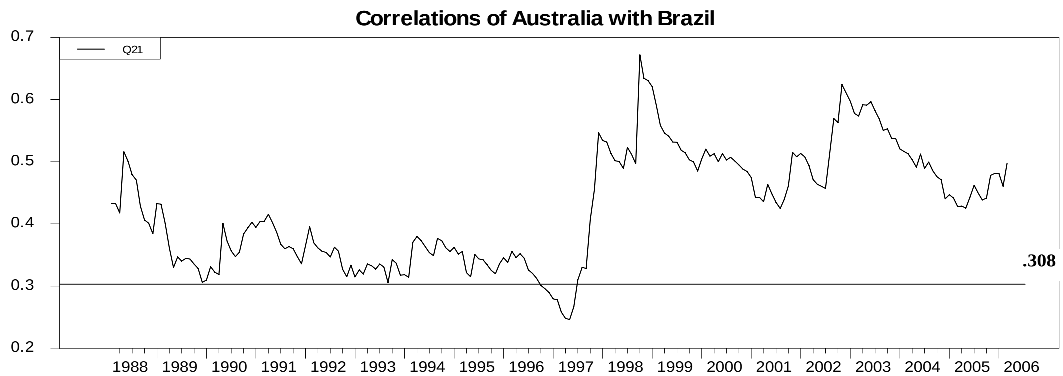
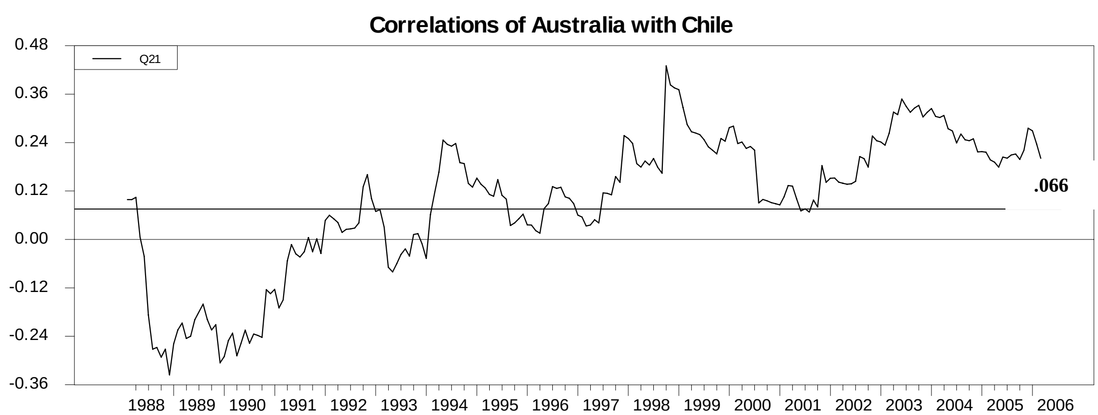
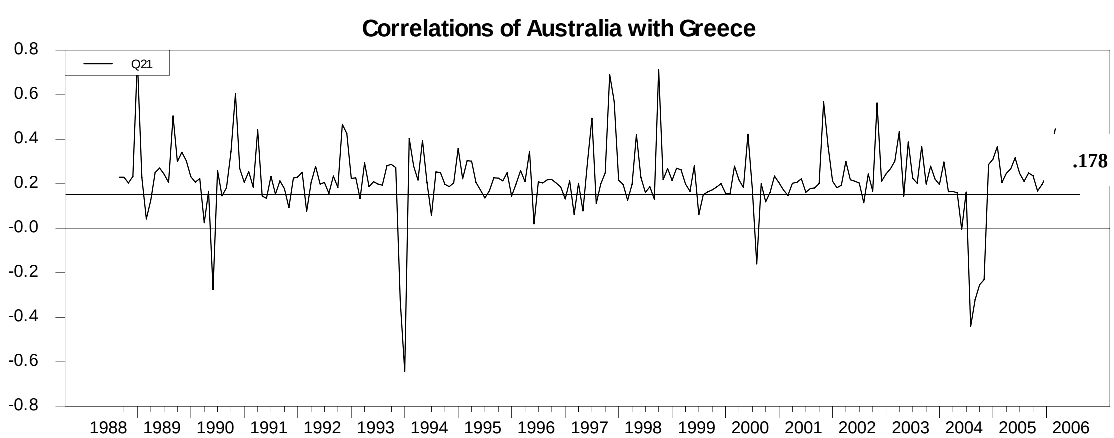
Annexure 1

Annexure 1: Graphs of time varying correlations of Australia with emerging markets.

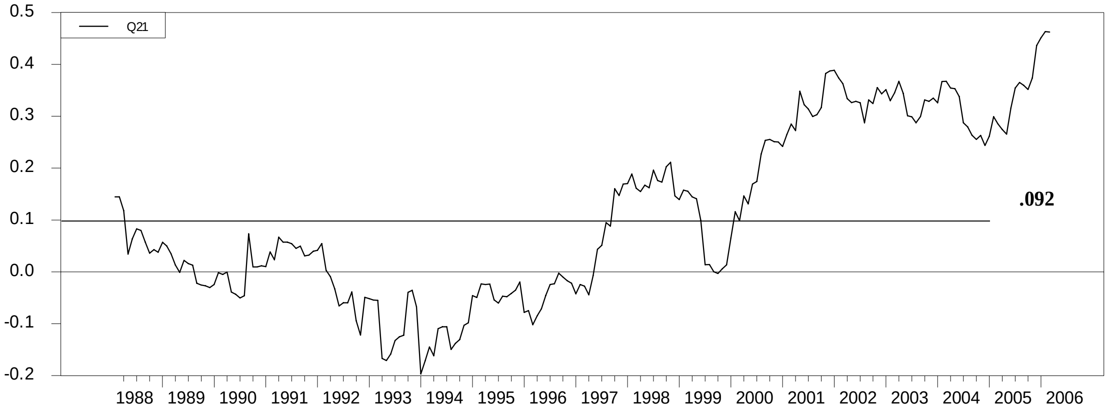




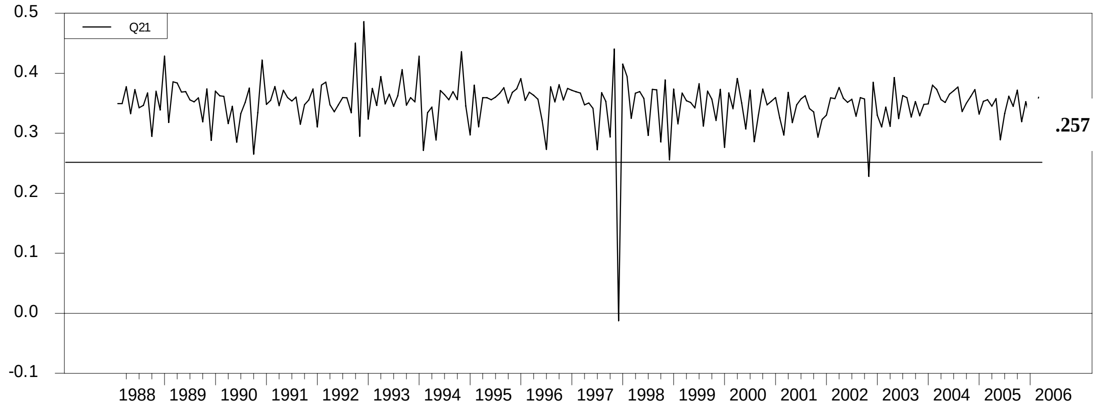




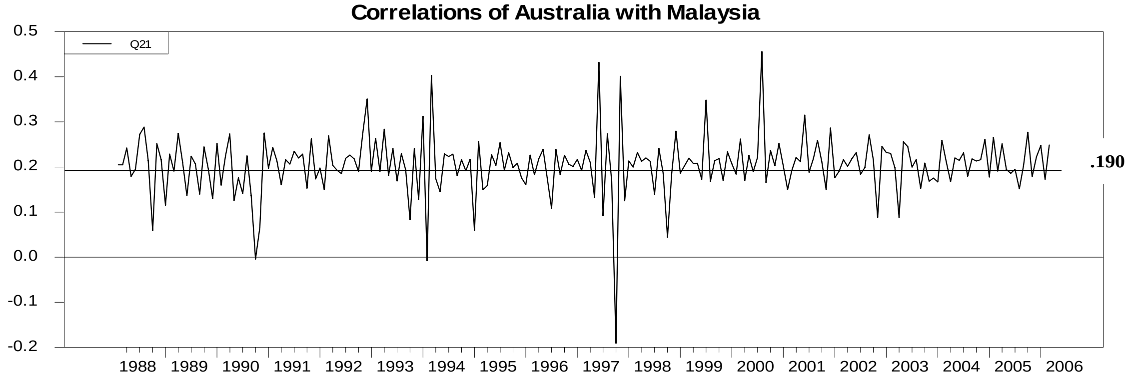
Correlations of Australia with India



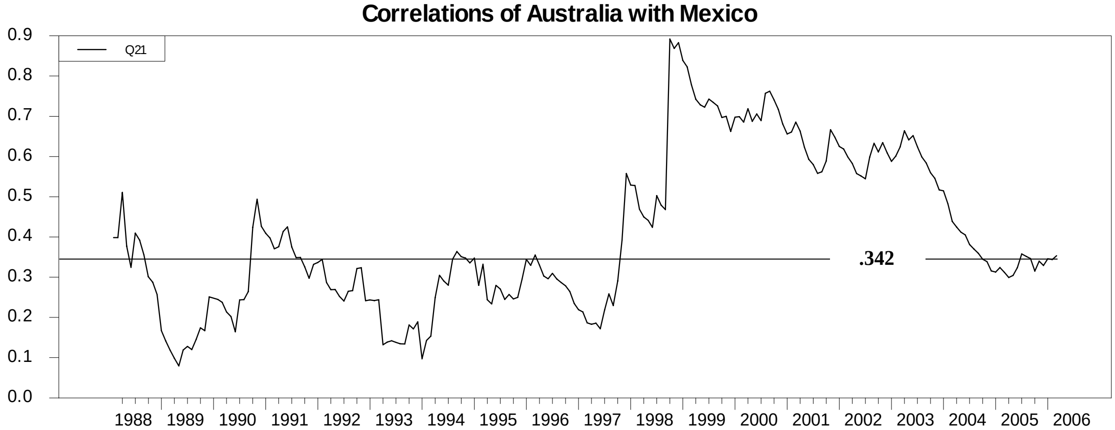
Correlations of Australia with Korea

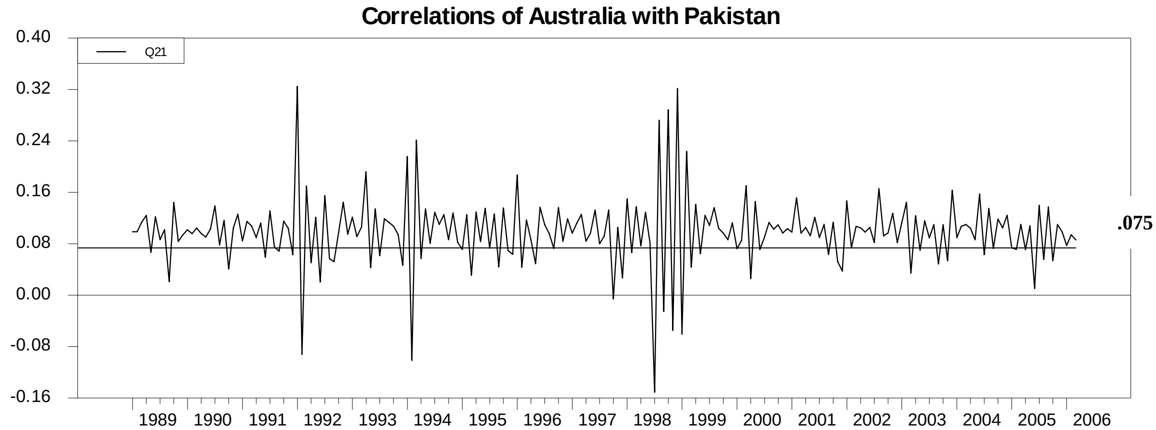


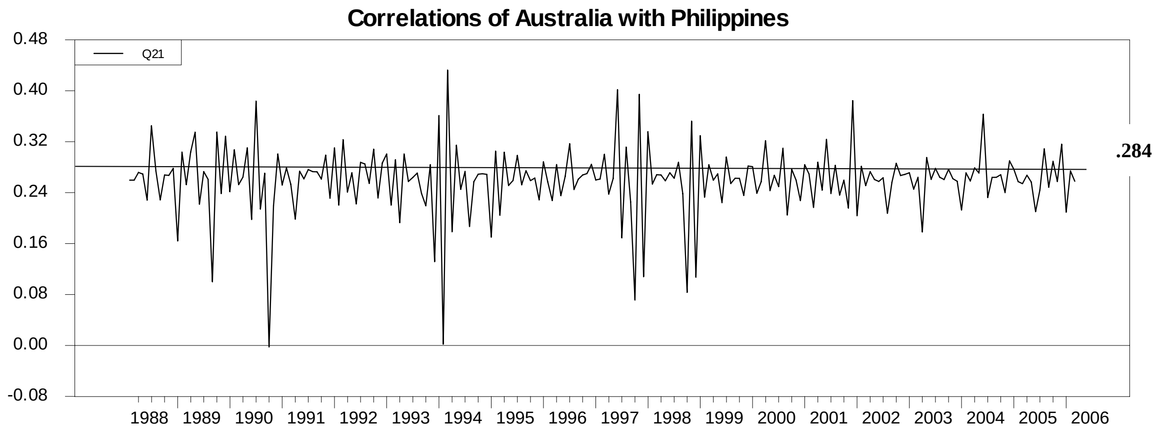
Correlations of Australia with Malaysia



Correlations of Australia with Mexico




Correlations of Australia with Pakistan
Q21
0.40
0.32
0.24
0.16
0.08
0.00
-0.08
-0.16
1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006
.075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Q21
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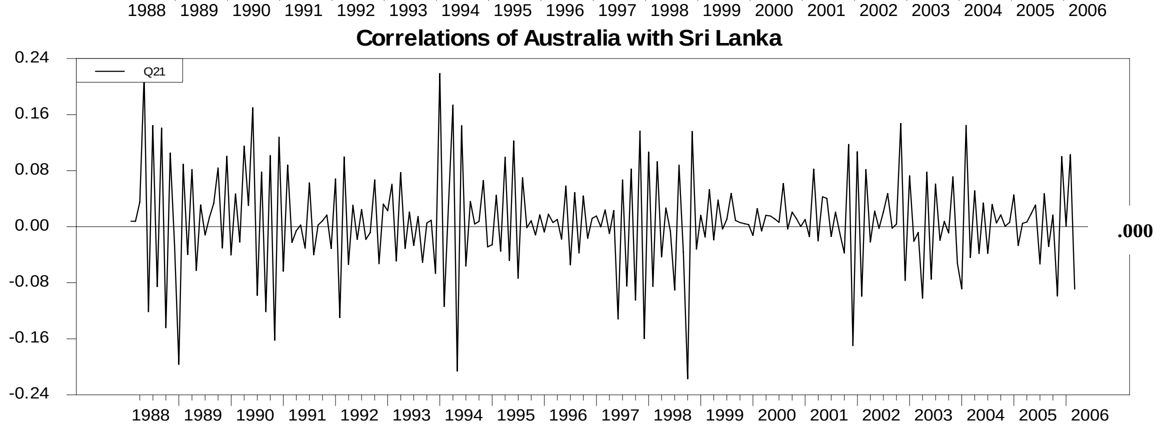
0.24
0.16
0.08
0.00
-0.08
1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006
.284


Correlations of Australia with Sri Lanka
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0.16
0.08
0.00
-0.08
-0.16
-0.24
1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006
.000

Annexure 2

Annexure 2: Regression results of factors affecting the correlation between Australian returns and emerging market returns (Asymmetric DCC GARCH).

Regression equation: $\rho_{i,t} = \alpha_i + \beta_1 Volatility_E + \varepsilon_t$

Market	Variable(Lags)	Coefficients	T-stat	no. of observations	Adj. R^2	Significance level of F
Brazil	Brzvol	- 0.7538	-3.3919*	213	0.0541	0.0008
Chile	Chivol	-8.0515	-3.3819*	213	0.2070	0.0000
	Chivol(1)	-6.5499	-2.6751*			
	Chivoll(2)	-6.3105	-2.7832*			
Korea	Korvol	1.5097	5.0881*	213	0.3505	0.0000
	Korvol(2)	1.5323	5.1542*			
Malaysia	Malvol(1)	-2.0701	-4.4954*	213	0.0924	0.0000
	Malvol(2)	1.0276	2.2286**			
Mexico	Mexvol(2)	0.9941	2.4856**	202	.02844	0.0137
Philippines	Phivol(2)	-3.2104	2.1126**	213	0.0207	0.0358

* significant at 1%, ** significant at 5% and *** significant at 10% level.

Variables are: Brzvol means volatility of Brazil market (emerging market), Ratio means ratio of volatility of emerging market to Australian market volatility, terms in brackets represent the lags.

Annexure 3

Annexure 3: Regression results of factors affecting the correlation between Australian returns and emerging market returns (Asymmetric DCC GARCH).

Regression equation: $\rho_{i,t} = \alpha_i + \beta_1 Volatility_{Aus} + \varepsilon_t$

Market	Variable(Lags)	Coefficients	T-stat	No. of observations	Adj. R^2	(Significance level of F)
Chile	Ausvol	-8.1648	-3.2119*	213	0.1757	0.0000
	Ausvol(2)	-5.9109	-2.3934**			
Greece	Ausvol(1)	4.3404	2.0818**	213	0.0606	0.0006
	Ausvol(2)	4.7052	2.2642**			
India	Aus	-7.0626	-2.3169**	213	0.0615	0.0004
	Ausvol(2)	-6.24355	-2.1300**			
Malysia	Ausvol	-2.2901	-2.4317**	213	0.0226	0.0000
Mexico	Ausvol	-2.4546	-2.8326*	213	0.0320	0.0050
Philippines	Ausvol(2)	-7.1925	-2.5337**	213	0.0730	0.0001
Sri Lanka	Ausvol(2)	-0.0297	-1.9867**	213	0.0137	0.0482
Turkey	Ausvol	-11.4919	3.8636*	213	0.0616	0.0001

* significant at 1%, ** significant at 5% and *** significant at 10% level.

Variables are: Brzvol means volatility of Brazil market (emerging market), Ratio means ratio of volatility of emerging market to Australian market volatility, terms in brackets represent the lags.

Annexure 4

Annexure 4: Regression results of factors affecting the correlation between Australian returns and emerging market returns (Asymmetric DCC GARCH).

Regression equation: $\rho_{i,t} = \alpha_i + \beta_1 \frac{Volatility_E}{Volatility_{AUS}} + \varepsilon_t$

Market	Variable(Lags)	Coefficients	T-stat	No. of observations	Adj. R^2	(Significance level of F)
Brazil	RBrz	-0.0048	-2.1721**	213	0.0450	0.0029
	RBrz(2)	-0.0040	-1.8230***			
Greece	RGre(2)	-0.0195	-2.2847**	213	0.0202	0.0233
Korea	RKor	0.0134	4.2369*	213	0.3703	0.0000
	RKor(1)	0.0090	2.5044**			
	RKor(2)	0.0070	2.2233**			
Malaysia	RMal(1)	-0.0165	3.4675*	213	0.0463	0.0025
	RMal(2)	0.0115	2.4278**			
Mexico	RMex	0.0093	2.6625*	213	0.0815	0.0000
	RMex(2)	0.0098	2.8072*			
Philippines	RPhi(1)	0.0255	2.1212**	213	0.0162	0.0350
Sri Lanka	RSri(2)	0.0000	1.7227***	213	0.0091	0.0864

* significant at 1%, ** significant at 5% and *** significant at 10% level.

Variables are: Brzvol means volatility of Brazil market (emerging market), Ratio means ratio of volatility of emerging market to Australian market volatility, terms in brackets represent the lags.

Annexure 5

Annexure 5: Diagnostic tests for the normality.

Market	Excess kurtosis	Jarque-Bera
Brazil vol	26.8906	7200.0977
Ratio	21.3142	4613.7407
Correlations	-0.1196	14.3927
Chile	2.9764	150.5640
Ratio	0.7871	30.3245
Correlations	-0.3061	16.6694
India	4.1262	250.6325
Ratio	4.9530	356.1710
Correlations	-0.5773	2.9931
Malaysia	17.8284	3352.9937
Ratio	13.1193	1869.0568
Correlations	10.6086	1082.3449
Mexico	9.7744	1131.7245
Ratio	5.5255	427.7248
Correlations	-1.1489	18.1497
Philippines	4.6514	319.6645
Ratio	5.3948	382.2111
Correlations	-0.2503	8.6971